NEW PROCEDURE FOR PROTOZOAN WHITE SPOT DISEASE DETECTION IN MARICULTURE FISH BASED ON ARTIFICIAL INTELLIGENCE

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NEW PROCEDURE FOR PROTOZOAN WHITE SPOT DISEASE DETECTION IN MARICULTURE FISH BASED ON ARTIFICIAL INTELLIGENCE

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ABSTRACT

Protozoan white spot disease, caused by *Cryptocaryon irritans*, poses a significant threat to marine fishes, resulting in a 100% mortality rate within a short period. Its impact extends beyond fish health, severely affecting commercial mariculture and causing substantial economic losses. The current standard procedure for early fish disease detection, reliant on time-consuming external gross observation, underscores the need for faster and more reliable automated approaches. In response to this issue, this study explores Artificial Intelligence (AI) as a transformative tool in fish disease detection. This study involved fine-tuning several convolutional neural networks (CNN) architectures including AlexNet, ResNet50, GoogleNet, ResNet101, and Vgg16Net to discern the most effective architecture for the proposed new procedure. Leveraging the success of CNN, particularly using the CNN's ResNet50 architecture, this study introduced a new procedure via integration of contrast-adaptive colour correction (CACC) with CNN for protozoan white spot disease detection using underwater images. Experimental finding reveals outstanding performance of the procedure, with the ResNet50 CNN architecture integrated with CACC achieving a testing accuracy of 99.52% on the acquired dataset, indicating that this new procedure holds immense promise in early fish disease prevention and intervention by providing an efficient and precise approach to protozoan white spot disease detection. While this experimental stage study demonstrates encouraging results, future endeavours should focus on extensive refinement and collaboration to elevate the procedure's readiness for on-site implementation. In summary, the integration of AI-driven techniques not only improves detection accuracy but also streamlines processes, potentially safeguarding marine fish populations and the aquaculture industry.

Keywords: Protozoan white spot disease, Mariculture, Underwater fish disease detection, Image enhancement, Convolutional neural network

ABSTRAK

Penyakit bintik putih protozoa yang disebabkan oleh *Cryptocaryon irritans*, merupakan ancaman besar kepada ikan marin, dan menyebabkan kadar kematian 100% dalam tempoh yang singkat. Kesannya melampaui tahap kesihatan ikan, mengancam marikultur komersial dan menyebabkan kerugian besar ekonomi. Prosedur standard semasa untuk pengesanan awal penyakit ikan bergantung kepada pemerhatian kasar luaran yang mengambil masa lama, menunjukkan keperluan untuk pendekatan automatik yang lebih cepat dan lebih dipercayai. Sebagai respon kepada permasalahan ini, kajian ini menerokai Kecerdasan Buatan (AI) sebagai alat bertransformasi dalam pengesanan awal penyakit ikan. Kajian ini melibatkan pelarasan semula beberapa senibina *convolutional neural network* (CNN) termasuk AlexNet, ResNet50, GoogleNet, ResNet101, dan Vgg16Net untuk membezakan senibina yang paling berkesan bagi prosedur baru yang dicadangkan. Dengan memanfaatkan kejayaan CNN, khususnya menggunakan senibina ResNet50 CNN, kajian ini memperkenalkan prosedur baru melalui integrasi *contrast-adaptive colour correction* (CACC) dengan CNN untuk pengesanan awal penyakit bintik putih protozoa menggunakan imej di bawah air. Penemuan eksperimen mendedahkan prestasi mengagumkan prosedur ini dengan senibina CNN ResNet50 yang berintegrasi dengan CACC mencapai ketepatan ujian sebanyak 99.52% pada dataset yang diperolehi. Ini menunjukkan prosedur baru ini memiliki potensi besar dalam pencegahan dan intervensi awal penyakit ikan dengan menyediakan pendekatan yang efisien dan tepat dalam pengesanan penyakit bintik putih protozoa. Walaupun kajian peringkat eksperimen ini menunjukkan hasil yang memberangsangkan, usaha pada masa hadapan harus memberi tumpuan kepada penghalusan dan kolaborasi yang meluas untuk meningkatkan kesiapan prosedur ini untuk pelaksanaan di lapangan. Secara ringkas, integrasi teknik-teknik berpandukan AI tidak hanya meningkatkan ketepatan pengesanan tetapi memperkemaskan proses sekaligus berpotensi melindungi populasi ikan marin dan industri marikultur.

Kata Kunci: Penyakit bintik putih protozoa, Marikultur, Pengesanan penyakit ikan bawah air, Peningkatan imej, *Convolutional neural network*

DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and any editorial work, paid or unpaid, carried out by a third party is acknowledged.

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AHE	Adaptive Histogram Equalization
AI	Artificial Intelligence
ALCC	Automatic Level Colour Correction
ARC	Automatic Red Channel
AWB	Auto White Balance
CACC	Contrast-Adaptive Colour Correction
BPN	Back-Propagation Network
CC	Colour Correction
C. irritans	*Cryptocaryon irritans*
CLAHE	Contrast Limited Adaptive Histogram Equalization
CIELAB	Commission Internationale de l'Éclairage LAB colour space
CNN	Convolutional Neural Network
CPN	Convolutional Prototype Network
CWT	Curvelet Wavelet Transform
DCP	Dark Channel Prior
DL	Deep Learning
DOF	Department of Fisheries
DOSM	Department of Statistics Malaysia
ENN	Elman Neural Network
ES	Expert System
EUS	Epizootic Ulcerative Syndrome
FAO	Food and Agriculture Organization
FAST	Features from Accelerated Segment Test
FB	Fusion-Based
FN	False Negative
FP	False Positive
FRI	Fisheries Research Institute
GDCP	Generalization Dark Channel Prior
GFSI	Global Food Security Index

GH	Greyscale Histograms
GLCM	Grey Level Co-Occurrence Matrices
HB	Hybrid
HOG	Histogram of Gradient
HSV	Hue, Saturation, Value
IBLA	Image Blurriness and Light Absorption
IP	Image Processing
KNN	K-Nearest Neighbours
LR	Logistic Regression
KNN	K-Nearest Neighbours
ML	Machine Learning
MSRCR	Multiscale Retinex with Colour Restoration
NaFisH	National Fish Health Research
NN	Neural Network
NLP	Natural Language Processing
ORB	Oriented Fast & Rotated Brief
PCA	Principal Component Analysis
PCQI	Patch-based Contrast Quality Index
PNN	Probabilistic Neural Network
PSNR	Peak Signal to Noise Ratio
RGB	Red, Green, Blue
RF	Random Forest
SIFT	Scale-Invariant Feature Transform
SURF	Speeded Up Robust Features
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TS	Two-Step
UDCP	Underwater Dark Channel Prior
UIBLA	Underwater Image Blurriness and Light Absorption
UIEB	Underwater Image Enhancement Benchmark
UKF	Unscented Kalman Filters

WSSV	White Spot Syndrome Virus
ZHC	Zone Health Centre

CHAPTER 1

INTRODUCTION

1.1 Overview of the Chapter

The background of the study is introduced in this chapter, providing context and rationale for the study. The problem statement is also presented in this chapter, highlighting the specific problems and challenges that the study aims to address. Additionally, these problems have led to the formulation of several research questions which are then addressed by the research objectives, specifying the specific inquiries and goals of the study. Next, the scope and limitation of the study are defined to outline the boundaries within which the study is conducted. Significance of the study and key terms used throughout the thesis are also defined, following with the organization of the thesis that provides an overview of each chapter.

1.2 Background of the Study

The aquaculture industry serves as a vital contributor to the Malaysia's food supplies, playing a substantial role in ensuring food security and economic stability in Malaysia. The demand for fish is experiencing continuous growth, driven by the expanding global population and fish is widely acknowledged for its exceptional nutritional value and its ease of digestion that is easily obtained (Maulu et al., 2021). As Malaysia moves towards the vision of creating smart communities by 2050, this industry has emerged as a rapidly thriving food industry. Malaysia, through its progress and innovative approaches, has successfully aligned itself with other Asian nations, collectively accounting for 42.0% of fish production in Asian aquaculture and projections indicate that by 2031, it is anticipated to supply 59% of the fish intended for human consumption, further solidifying its position in the global aquaculture landscape (Food and Agriculture Organization [FAO], 2020). Furthermore, the total aquaculture production in Malaysia witnessed significant progress, reaching approximately 411,800 tonnes in 2019, represents an increase of 5.2% compared to the production in 2018 (Department of Statistics Malaysia [DOSM], 2020). According to the Global Food Security Index (GFSI) 2022, Malaysia has been ranked 41st with a score of 69.9% which indicates a positive level of food security, particularly regarding aquaculture production, as reported by the Economist Impact in 2022. In addition, fish consumption per head in this country was estimated to be 59 kg and among the highest fish demand in the world (FAO, 2020) . Thus, Malaysia is greatly dependent on fish production as a source of protein supplies to meet the country's demand of 32.70 million inhabitants. As the forecasted decline in capture fisheries due to overfishing looms and the demand for fish consumption continues to rise, the aquaculture industry is emerging as a prominent solution to ensure a sustainable fish supply. Alternatively, aquaculture is viewed as an option to lessen the pressure on capture fisheries and provide employment and investment opportunities. Therefore, much effort should be put forward in making aquaculture industry economically and ecologically viable for the sustainability of fish production.

Finfish mariculture is one of Malaysia's fastest expanding aquaculture industries (Khoo et al., 2012; Larson et al., 2023). Nonetheless, research has revealed that fish disease is one of the major constraints, limiting industry productivity and sustainability that subsequently impact the livelihood of farmers, food safety, job security, and income (Ali et al., 2020; Assefa & Abunna, 2018). It is estimated that approximately 15% of fish production is reduced annually due to diseases (Mia et al., 2022), which poses significant challenges for breeders, particularly in developing countries, as their investments are at risk of being paralyzed. Particularly during the hatchery and nursery stages, parasitic infections are associated with protozoan parasites (Faruk & Anka, 2017; Kua, 2008, 2014; Nagasawa & Cruz-Lacierda, 2004; Saha & Bandyopadhyay, 2017). *Cryptocaryon irritans*, a protozoan parasite is indeed an obligate ectoparasite causing *cryptocaryonosis* (commonly known as "protozoan white spot disease") including those in the wild, ornamental fish, and culture setting (Priya et al., 2012; Van & Nhinh, 2018). This disease normally develops on the outer layer and characterized as small white spots, discoloration, ragged fins, cloudy eyes, pale gills, excessive mucus production and appear thin due to damage caused by the *C. irritans* (Chi et al., 2020; Yanong, 2017). Its extensive spread, random host selection, and high level of severity result in significant destruction to the commercial mariculture industry (Cheng et al., 2020). Moreover, ectoparasites like *C. irritans* could significantly harm the initial defence mechanisms, potentially provide entry points for other pathogens like bacteria and viruses to invade and infect the affected fish. Due to its rapid escalation in mortality rates over a span of several days (Colorni & Burgess, 1997; Iaria et al., 2019), this study primarily emphasizes on protozoan white spot disease.

Detecting fish diseases at the early stages is crucial for containing the spread and preventing re-emergence as emphasized by Waleed et al. (2019), because a delayed detection of the diseases could lead to the complete loss of all the fish in the affected population. Hence, early detection plays a critical role in minimizing potential losses to fish farm. According to the standard procedure, early detection of fish disease involves external gross observation by fish experts through human visualization. This external gross observation required experts to possess the requisite knowledge and expertise to detect fish diseases accurately (Divinely et al., 2019; Malik et al., 2017a; Waleed et al., 2019). While fish experts have the expertise to detect diseases based on their knowledge and experience, the process itself is tedious, leading to unintended delays and potentially escalated mortality rates. Hence, there is a pressing need for an efficient, non-destructive, and immediate early detection procedure to maintain fish health and safety, as well as to prevent the spread of diseases within the aquaculture industry.

The technological revolution presents an opportunity to develop intelligent, minimally invasive computer-aided procedures that could address or reduce issues associated with standard human intervention-based procedures. Professionals across various fields, including radiologists, surgeons, and endoscopists, are increasingly adopting computer-aided procedures in their practices. The development of these procedures has been influenced by several factors, such as advancements in imaging, enabling pioneers to perform procedures with the assistance of “image guidance”. The rising interest in Artificial Intelligence (AI) is facilitating the adaptation and implementation of image-guidance technologies in the field of fish disease detection, making minimally invasive procedures highly compelling. Numerous publications have reported on the application of AI methods that employ various image processing, machine learning (ML), and deep learning (DL) techniques (Ahmed et al., 2021; Divinely et al., 2019; Muhammad Luqman et al., 2022; Noraini et al., 2022; Waleed et al., 2019). Indeed, the availability of AI methods has opened the door for a great opportunity to enhance the long-term performance of timely fish disease detection. This study aims to provide early detection of protozoan white spot disease by introducing a new procedure utilizing the AI method at the cutting edge of technology-driven “automation, smart and intelligent system” of Fourth Industrial Revolution (IR 4.0).

1.3 Problem Statement

In the context of early detection of fish diseases, it often relies on external gross observation where during the process of standard procedure, this observation involves fish experts conducting observation using their eyes as the primary tool. Nevertheless, this is a challenging process since it necessitates a high level of expertise to ascertain the accurate detection (Divinely et al., 2019; Malik et al., 2017b; Waleed et al., 2019). The limitation become evident as external gross observation heavily relies on the cumulative knowledge and skills of domain experts, making it prone to judgmental errors, inconsistencies, and longer time lags between observations (Adl & Younan, 2019; Darapaneni et al., 2022; Hitesh et al., 2015; Muhammad Luqman et al., 2022; Noraini et al., 2022). Moreover, ensuring the availability of fish experts for external gross observation during on-site investigation is crucial. However, due to the remote locations of fish farming sites, it becomes impractical for fish experts to reach these areas in a timely manner. In certain cases, this observation takes place in a laboratory setting. Although laboratory setting offers the advantage of controlled conditions, they are accompanied by the drawback of prolonged time demands which could potentially hinder quick decision-making and timely interventions, especially in situations where immediate responses are of utmost significance. Considering the limitations of external gross observation in standard procedure for fish disease detection highlight the need for improved technological approach to achieve early and timely detection. While recent advancements have brought about significant progress in fish disease detection, challenges remain, including existence of various fish species, limitations in input datasets, and the complexities of the underwater environment. Overcoming these challenges will be crucial in developing effective fish disease detection.

The success of underwater applications is closely tied to the quality of the captured underwater images which is significantly influenced by the underwater environment and the characteristics of the objects being observed (Soni & Kumare, 2020; Zhang et al., 2019). Challenges arise due to the underwater images under an unconstrained environment, impacting image quality through factors like poor contrast, poor visibility, colour distortion and non-uniform (Raveendran et al., 2021; Song & Wang, 2021). Light absorption and scattering underwater result in image loss and noise, complicating accurate analysis (Almutiry et al., 2021; Natarajan, 2017; Prasath & Kumanan, 2020). Even with artificial light sources, limitations persist, leading to flash spot at the centre of the image, surrounded by poor lighting conditions (Galdran et al., 2015; Muñoz et al., 2023; Yang et al., 2019). Consequently, underwater images captured by cameras are affected by poor visibility, uneven lighting, blurring, and colour distortion.

To address the challenges associated with underwater environments, various image enhancement (IE) techniques such as dark channel prior (DCP), contrast limited adaptive histogram equalization (CLAHE), and colour correction (CC) have been introduced. It is worth noting that while these techniques address specific issues in underwater imaging, they may not comprehensively solve all the challenges faced (Wang et al., 2020). Also, certain studies have overlooked the issue of noise generated by these algorithms (Pati et al., 2018). This oversight adds complexity to the challenge of achieving high quality underwater image, warranting further attention and refinement in the enhancement techniques to address this specific concern. Additionally, most studies concentrate on enhancing the visual quality of underwater images and do not explicitly consider the impact on the performance of underwater classification applications, instead the primary focus often lies in background removal for feature extraction purposes (Pramunendar et al., 2019). Therefore, it is essential to evaluate the adaptability of the enhancement technique in conjunction with classification method to determine their effectiveness in improving the classification accuracy in underwater image application, specifically for fish disease detection.

The utilization of ML for fish disease detection often relies on hand-engineered feature extraction techniques like histogram of gradient (HOG), scale-invariant feature transform (SIFT), greyscale histograms (GH), grey level co-occurrence matrices (GLCM), and features from accelerated segment test (FAST) to extract crucial features such as texture, shape, and colour from images. While these methods exhibit efficient performance, their dependence on expert-crafted feature selection introduces vulnerability to biased or inappropriate choices, consequently diminishing the accuracy of distinguishing between disease classes (Taye, 2023). As the number of distinct classes increases, the complexity of feature extraction escalates, constraining adaptability to new datasets (Bengio et al., 2013; O' Mahony et al., 2019). Moreover, these techniques often display reduced resilience when faced with images characterized by either low-contrast or high-contrast conditions (Khai et al., 2022). Traditional ML techniques like support vector machines (SVM), logistic regression (LR), k-nearest neighbours (KNN), random forest (RF), and probabilistic neural networks (PNN) have showcased proficient classification performance in specific data scenarios. However, their effectiveness heavily hinges on the precise extraction of well-defined features from the data (Janiesch et al., 2021). Notably, these supervised ML methods necessitate substantial human involvement for learning and error correction, leading to overfitting risks when trained on limited data volumes (Ghojogh & Crowley, 2019; Taigman et al., 2014; Taye, 2023; Ying, 2019).

In summary, the standard procedure to early fish disease detection relying on external gross observation is inherently flawed due to its susceptibility to inaccuracies and time-consuming. Moreover, when dealing with underwater images, a various of challenges arises, encompassing issues such as poor visibility, contrast, colour distortion, and haze. These obstacles often remain unaddressed or inadequately managed by existing image enhancement techniques, which may not effectively enhance classification performance. Meanwhile, when it comes to classification tasks, ML techniques may fall short, particularly when it requires significant human intervention to learn and extract the features. To address these multifaceted challenges and limitations, a new procedure for detecting protozoan white spot disease is done, integrating Contrast Adaptive Contrast Correction (CACC) with Convolutional Neural Networks (CNN) as an AI method. The core objective of this new procedure is to transcend the constraints of early fish disease detection while significantly elevating the accuracy of disease detection within underwater environments.

1.4 Research Questions

Considering the issues discussed previously, it becomes evident that further research is necessary in the field of protozoan white spot disease detection studies. Aside from generating new ideas for development, this study aims to identify and address the limitations and gaps in the existing research. Consequently, the study intends to tackle these challenges by exploring the following research questions:

i. What are the morphological features of protozoan white spot disease in mariculture fish?

ii. How to develop new procedure via integration of CACC with CNN for detection of protozoan white spot disease using underwater images?

iii. What is the performance of proposed new procedure?

1.5 Research Objectives

The primary goal of this study is to introduce a new procedure for detecting protozoan white spot disease using underwater images. To accomplish this goal, several specific objectives are required to be met, including:

i. To identify the morphological features of protozoan white spot disease in mariculture fish.
ii. To develop a new procedure via integration of CACC with CNN for detection of protozoan white spot disease using underwater images.
iii. To evaluate the performance of proposed new procedure.

1.6 Scope and Limitation of the Study

This study's scope is divided into three distinct areas, delineated as the domain area, the technological approach area, and the technical area, as illustrated in Figure 1.1, Figure 1.2, and Figure 1.3, respectively. The domain interest in this study is protozoan white spot disease, a parasitic infection. The underwater fish image dataset acquired in this research was obtained from experiments conducted at the National Fish Health Research (NaFisH) Batu Maung in Pulau Pinang. Also, this study takes into account image-based automatic system as one of the existing technological approaches for fish disease detection. Using underwater images, this study concentrated on the development of integration between image enhancement and DL for detection of protozoan white spot disease.

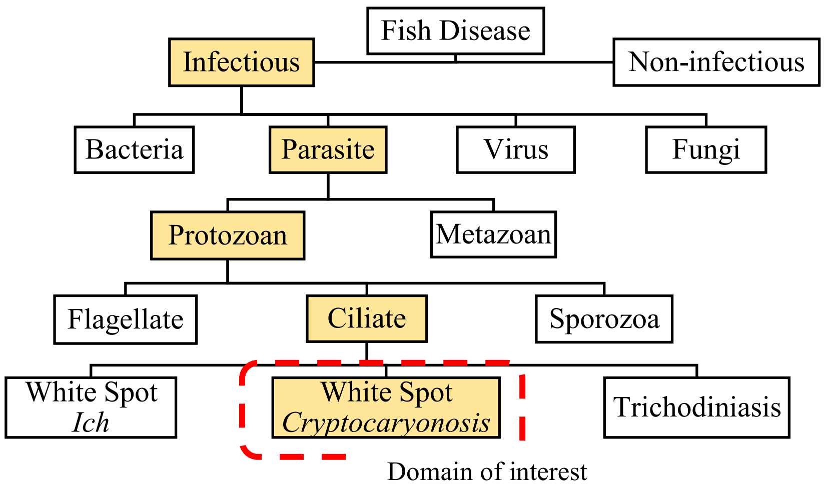


Figure 1.1: *Hierarchy Chart Area Domain of Interest in the Study*

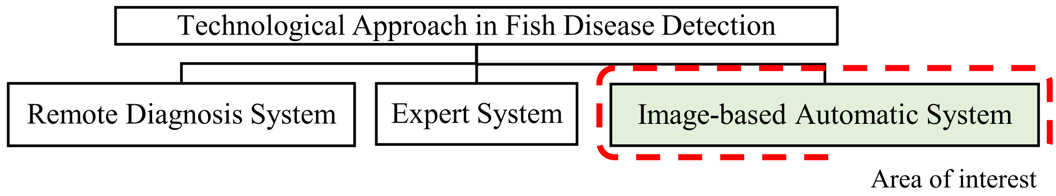


Figure 1.2: *Hierarchy Chart Area Technological Approach of Interest in the Study*

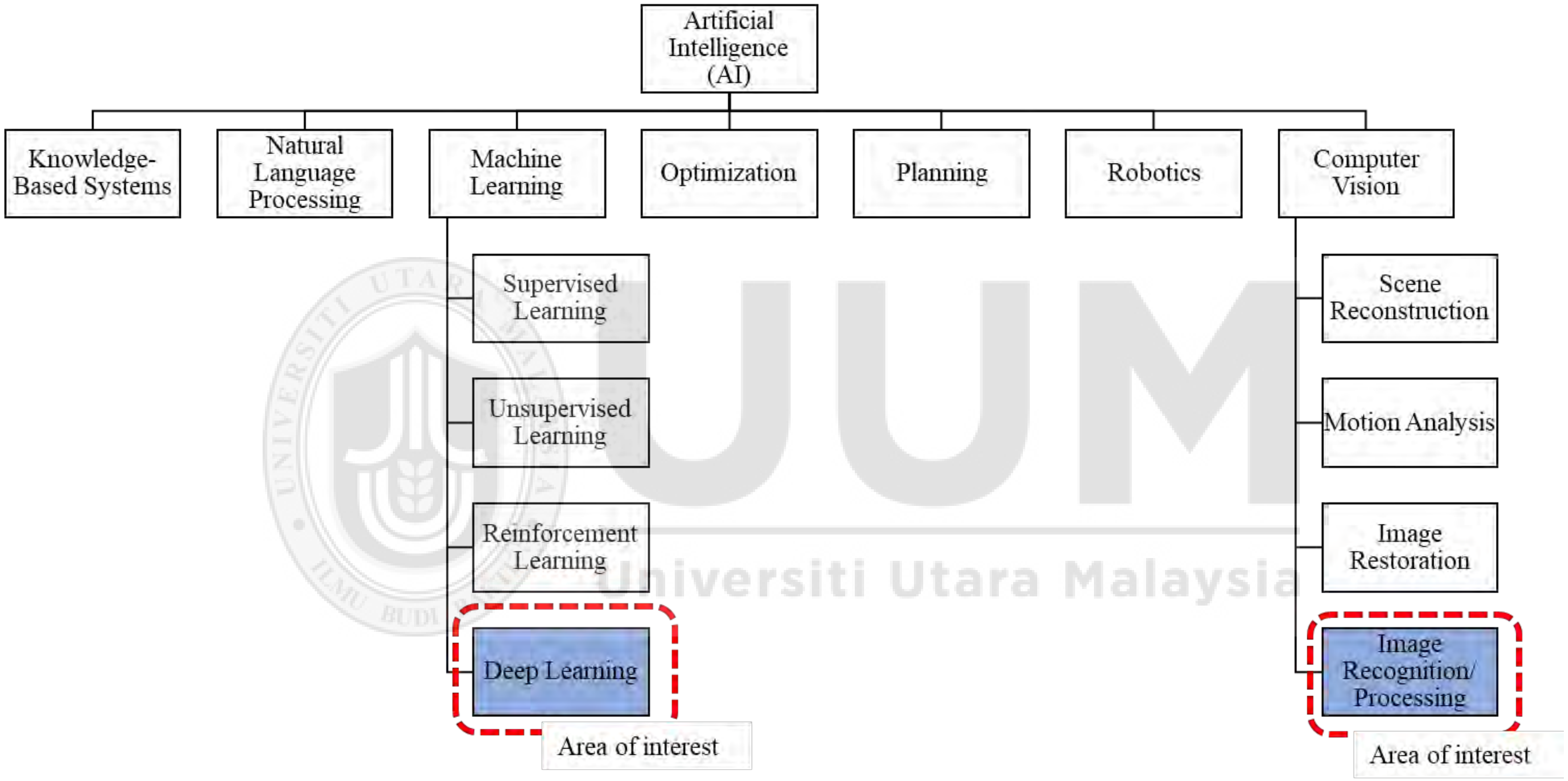


Figure 1.3: *Hierarchy Chart Technical Area of Interest in the Study*

To effectively work towards accomplishing the defined objectives, it is essential to establish specific limitations that outline the scope of this study. White spot disease can manifest in diverse forms, stemming from different sources: one variant is caused by a virus, another by a bacteria, and another by a parasite. This study is narrowed to focus exclusively on white spot disease caused by the protozoan parasite, specifically excluding the viral infection referred to as white spot syndrome virus (WSSV), which primarily affects decapod crustaceans, and the bacterial infection referred to as bacterial white spot syndrome (BWSS), which affects shrimp. Furthermore, the investigation in this study pertains to protozoan white spot disease within mariculture, with its origin attributed to the parasite *Cryptocaryon irritans*. Consequently, white spot disease affecting freshwater cultured fishes due to the parasite *Ichthyophthirius multifiliis* is not covered in this study. It is essential to underscore that this study is delimited to the image-based detection of fish disease, primarily relying on the morphological features of external symptoms exhibited on the fish's body. Thus, the behavioural aspects of fish are not explored within this study's framework.

Currently, there is an absence of publicly accessible dataset containing images of mariculture fish affected by protozoan white spot disease. In response to this gap and with the intent to facilitate further research, this study has initiated the creation of its dataset. The acquisition procedure is conducted within a laboratory setting to facilitate this effort. Given the challenging and time-consuming nature of the process involved in creating a dataset containing protozoan white spot infected fish, this study focuses exclusively on one fish species, seabass. The primary aim is to provide early detection of fish disease, thus emphasizing a comparison between the proposed procedure and the external gross observation employed in the standard procedure. Additionally, this study focuses on evaluating the performance of classification when combined with image enhancement techniques. Therefore, the study does not specifically focus on evaluating the performance of image enhancement techniques in isolation. Lastly, it is important to acknowledge that the selection of individuals for the survey questionnaire as part of performance evaluation may introduce a certain limitation, potentially affecting the richness of research data.

1.7 Significance of the Study

Upon the completion of this study, it is anticipated that the findings will hold significant value for both the academic community and practitioners in the field. Theoretically, this study is expected to expand the existing body of knowledge and offer empirical validation within the realm of technology management as this study introduces a new procedure for the detection of protozoan white spot disease based on underwater images. This new procedure has the potential to mitigate or address issues associated with standard human intervention-based procedures. Additionally, it aids in the monitoring of fish diseases, particularly by enabling early detection of infection caused by parasites using AI methods. Early detection of this infection not only helps prevent co-infection with other pathogens but also serves as a proactive measure to avoid unintended delays that could potentially escalate mortality rates within aquaculture environments.

These findings also could assist fish experts and fish farmers in enhancing the detection process, aligning with the imperatives of the IR 4.0. Moreover, this study has a potential to foster closer collaboration between industry stakeholders, government agencies, and universities, with the aim of upskilling individuals with an embedded technology strategy mindset. In the long term and in alignment with Sustainable Development Goals (SDGs), this study could support the sustainable development of the aquaculture industry, particularly focusing on two critical aspects: income generation and sustainability.

1.8 Definition of Key Terms

This subsection provides definitions for the terms utilized in this study, aiming to enhance the clarity of the study's context. The terms covered include:

i. **Procedure**

   Procedure refers to a series of steps or actions taken to accomplish a specific task or objective. Designed to ensure consistency, efficiency, and accuracy in performing tasks that might be complex or require a particular order of actions.

ii. **Computer-aided**

   Computer-aided refers to the integration of computers or computer technology to assist, enhance, or automate various tasks or processes across different fields and industries. This term implies that computers play a significant role in improving the efficiency, accuracy, or capabilities of a particular activity.

iii. **Disease detection:**

   Disease detection refers to an action or process of identifying the presence of a certain abnormal condition that is associated with alteration of the normal structural or functional state of all or a part of an organism. It is frequently referred to as the discovery of something characterized by a specific set of signs and symptoms.

iv. **Underwater imaging:**

   Underwater imaging refers to the collection and processing of images and videos taken from underwater environments. Specialized equipment and techniques are commonly involved during the process of taking underwater images.

v. **Artificial Intelligence (AI):**

AI is used to describe a digital computer or computer-controlled robot that can execute tasks dealing with intelligent beings. Intelligence is characterised by the ability to adapt to changing circumstances.

vi. **Image enhancement:**

Image enhancement refers to the process of adjusting or manipulating original digital images so that the images are more suitable for display or further image analysis.

1.9 Organization of the Thesis

This study is organized into five chapters, which are as follows: the introduction, the literature review, the methodology, the results and discussion, and the conclusion and recommendations. These chapters collectively address the research problem and research issues in the following manner:

Chapter 1: This chapter discusses the introduction of the whole study. It covers the background of the study, problem statement, research questions, research objectives, the scope of the study, the significance of the study, the definition of the key terms and the organization of the thesis.

Chapter 2: This chapter discusses the literature review which presents the overall overview and evidence related to the current study. It includes a literature review of fish disease outbreak in mariculture, protozoan white spot disease, underwater imaging, underwater image enhancement, an AI application in fish disease detection, and performance evaluation.

Chapter 3: This chapter discusses the methodology of the method which presents the development of the new procedure via integration of image enhancement and DL. The methodology includes fish image acquisition, morphological feature identification, new procedure development, and performance evaluation.

Chapter 4: This chapter discusses the findings of the study. It presents complete results and analyses of new procedure via integration of image enhancement and DL.

Chapter 5: This chapter discusses the conclusions observed from results obtained. Finally, future work is recommended for the proposed procedure for early detection of protozoan white spot disease and broader applications are considered

CHAPTER 2

LITERATURE REVIEW

2.1 Overview of the Chapter

This chapter is divided into nine sections. The subsequent section presents an overview of fish disease outbreak and standard procedure for fish disease detection, followed by a discussion on the protozoan white spot disease. Section four presents computer-aided approach in fish disease detection. Section five explores the challenges associated with underwater imaging. Next, several existing algorithms used in underwater image enhancement are reviewed in section six. Section seven provides a general overview of ML and DL within the context of AI, followed by an overview of existing image-based AI applications in fish disease detection. Section eight presents an overview for the performance evaluation. Finally, the chapter concludes with a summary in the last section.

2.2 Issue in Mariculture

In 2020, world fisheries production reached a record of approximately 177.8 million tonnes, with aquaculture production accounting for 87.5 million tonnes (49.2%) and capture production accounting for 90.3 million tonnes (50.8%) of total production (FAO, 2022). Over the last few decades, a significant portion of the world's fish resources has been depleted, and as a result, world fisheries are unable to sustain the maximum output of the production. Fisheries sector plays an important role as the main contributor of protein source to meet the country's demand of 32.70 million inhabitants with 60-70% to the total source. Moreover, the aquaculture industry in Malaysia has rapidly developed during the last few decades and has positioned the top 15 of the world's producers in terms of aquaculture production (FAO, 2016).

According to the World Bank in 2022, the aquaculture sector, alongside other agricultural sectors, played a significant role in Malaysia's gross domestic product (GDP) in 2021 as it accounted for approximately 10% of the country's GDP. This highlights the economic importance of the aquaculture industry within Malaysia's overall economy. However, when examining the total capture and aquaculture sectors, as shown in Figure 2.1, there has been relatively minor fluctuation in growth from 2018 to 2021, according to data from FAO in 2022.

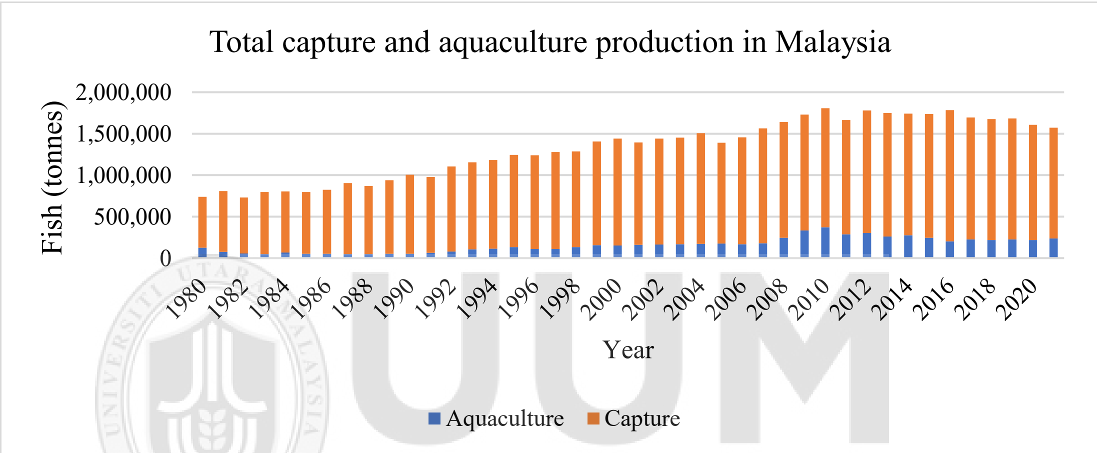


Figure 2.1: *Total Capture and Aquaculture Production in Malaysia*
Reproduced from FAO (2022)

The mariculture of finfish is one of the most rapidly expanding industry in Malaysia's aquaculture industry (Khoo et al., 2012; Larson et al., 2023). In Malaysia, mariculture of Asian sea bass (*Lates calcarifer*) is a valuable industry making the largest contributor of cultured species, followed by grouper (*Epinephelus spp.*), John's snapper (*Lutjanus johnii*) and mangrove red snapper (*Lutjanus argentimaculatus*) (Aishah, 2015; Mohd Syafiq et al., 2022; Shaharah et al., 2022). These cultured fish are often cultured inland or sea areas such as cages, ponds, or raceways (Ahmed et al., 2021). The growing production of mariculture has great potential to continuously sustain the protein demand of the growing human population in this country. For that reason, several initiatives have been taken in this industry, including genetics breeding program, culture systems technology, aquaculture best management practice, and aquaculture feed (Sharihan et al., 2018). Unfortunately, as these continue to grow, several issues emerge from current practices with the intensification and increment in aquaculture production (Chiew et al., 2019). One of the most overwhelming threats is the spread of contagious diseases that deteriorates the production of the culture species and disrupt the long-term sustainability of aquaculture (Assefa & Abunna, 2018; Chiew et al., 2019; Kua et al., 2013). Infected diseases have a detrimental impact on fish production, leading to a decrease in both quantity and quality.

2.2.1 Fish Disease Outbreak

Rapid and uncontrolled development of aquaculture has resulted in disease outbreaks affecting the industry's long-term sustainability. Disease occurrence and outbreaks become a primary issue given the potential to wipe out fish populations, aided by the ease with which diseases can be transmitted through aquatic environments (Leung & Bates, 2013; Manna et al., 2022). Moreover, the large number of fishes concentrated in a closed space encourages for development and rapid spreading of contagious diseases (Ahmed et al., 2021). Fish are stressed and more susceptible to disease when they are crowded in a closed space. Consequently, fish farmers bear massive monetary losses in terms of investment due to dead fishes, additional treatment costs, and a decrease in growth during the recovery period (Assefa & Abunna, 2018; Stentiford et al., 2012; Tacon & Metian, 2013).

Fish mortality is heavily influenced by disease, particularly in young fish (Sharma et al., 2012). According to Soni et al. (2021), parasites, viruses, bacteria, and fungi infections are the common pathogenic agents causing infectious diseases. Non-infectious diseases, on the other hand, are the result of environmental factors, dietary inadequacies, or a genetic abnormality (Admasu & Wakjira, 2021). Unfavourable environmental conditions include overcrowding, poor farm hygiene, salinity fluctuations, inadequate dissolved oxygen, high concentrations of obnoxious gases like hydrogen sulphide, carbon dioxide and ammonia, or harmful toxins (Alfred & Shaahu, 2020; Raman et al., 2013). Disease occurrence often arises from intricate interactions encompassing the host, the pathogen, and environmental factors, as illustrated in Figure 2.2 (Moreira et al., 2021). The development and severity of fish diseases are affected by a combination of variables including water condition, temperature, stress levels, nutrition, immune response of the host, and virulence of the pathogen. Understanding the intricate dynamics between the host, pathogen, and environmental variables is essential for crafting successful disease management and prevention strategies, thus, the task of fish disease detection can be considered challenging due to the intricate nature of the disease itself.

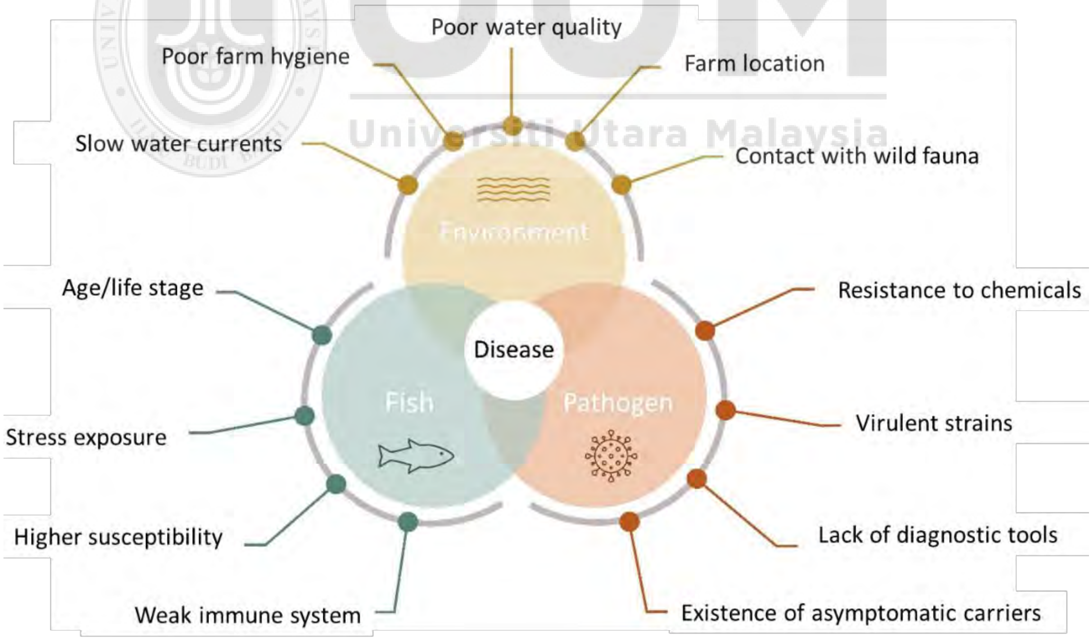


Figure 2.2: *Occurrence of Fish Disease*
Source: Moreira et al. (2021)

2.2.2 Standard Procedure Fish Disease Detection

The collection of data on fish mortality cases primarily relies on two sources: direct reports from farmers and referrals from the State Fisheries Office or Fisheries Biosecurity Division. These cases are documented through a standardized form as part of the National Fish Health's operational procedure involving the main centre located at the Fisheries Research Institute (FRI), Batu Maung, and other centres such as the Zone Health Centre (ZHC) as shown in Figure 2.3 (Reproduced from Afzan Muntaziana et al., 2018). Upon concluding the investigation and identifying the cause of death, an official report is generated. This report is then issued to the fish breeder through the state fisheries district office within a timeframe of two weeks after the investigation period has ended. In summary, the standard procedure for fish mortality cases involves receiving reports from farmers or referrals, conducting investigations by research officers, determining the cause of death, providing appropriate treatment measures, and issuing an official report to the fish breeder within two weeks of the investigation's completion.

Fish disease is devastating as it transmits rapidly from one fish farm to another (Alaimahal et al., 2017). Detecting fish diseases at their early stages is crucial for containing the spread and preventing re-emergence, as emphasized by Waleed et al. (2019), thus early detection plays a vital role in minimizing losses to the entire fish farm. When diseases are detected late, infected fish can continue to interact with healthy individuals, leading to the further spread of the disease within the population. This not only affects the health and well-being of the fish but also results in significant economic losses. Early detection of fish disease according to the standard procedure is commonly conducted through external gross observation by fish experts through human visualization (Figure 2.4) (Reproduced from Kua et al., 2019). In the context of investigating fish mortality cases, research officers at the NaFisH are responsible for conducting these investigations, as depicted in Figure 2.5 (Reproduced from Afzan Muntaziana et al., 2018), highlighting the role of these experts in analysing and addressing fish disease detection. After all, the external gross observation required experts to possess the necessary knowledge and expertise to identify and diagnose various fish diseases or health issues accurately (Divinely et al., 2019; Malik et al., 2017a; Waleed et al., 2019).

Function

National Fish Health Management Committee

* Fisheries Department

1. LIKM
2. DOE
3. UPM
4. USM

Function:

1. Monitor and investigate fish disease and mortality problems
2. Provide guidance and assistance to stakeholders in resolving fish disease problems

↓

Main centre

Pulau Pinang (Fisheries Research Institute)

Function:

1. Database
2. Networks with other agencies
3. Collaboration with UPM/USM
4. Serve as an information centre/advice service

↓

Zone centre

(a) Fisheries Research Institute (FRI), Pulau Pinang

(b) FRI Branch

* PPPBUK, Pulau Sayak, Kedah
* PPIAT, Batu Berendam, Melaka
* PPTAP, Gelang Patah, Johor
* PPPIL, Tanjung Demong, Terengganu

(c) Aquaculture Branch

* Quarantine And Fish Health Center
* Aquaculture Development Centre

Function:

1. Conduct research and identify disease-causing agents/causes of mortality
2. Implement on-site treatment measures
3. Monitor the occurrence of disease

↓

Mainroot supervision network

* State Fisheries Office
* District Fisheries Assistant

Function:

1. Conduct an initial investigation
2. Complete and submit the appropriate A1, A2, or A3 forms to ZHC & FRI
3. Interact with ZHC for further treatment and necessary actions

Figure 2.3: *National Fish Health's Modus Operandi*
Reproduced from Afzan Muntaziana et al. (2018)

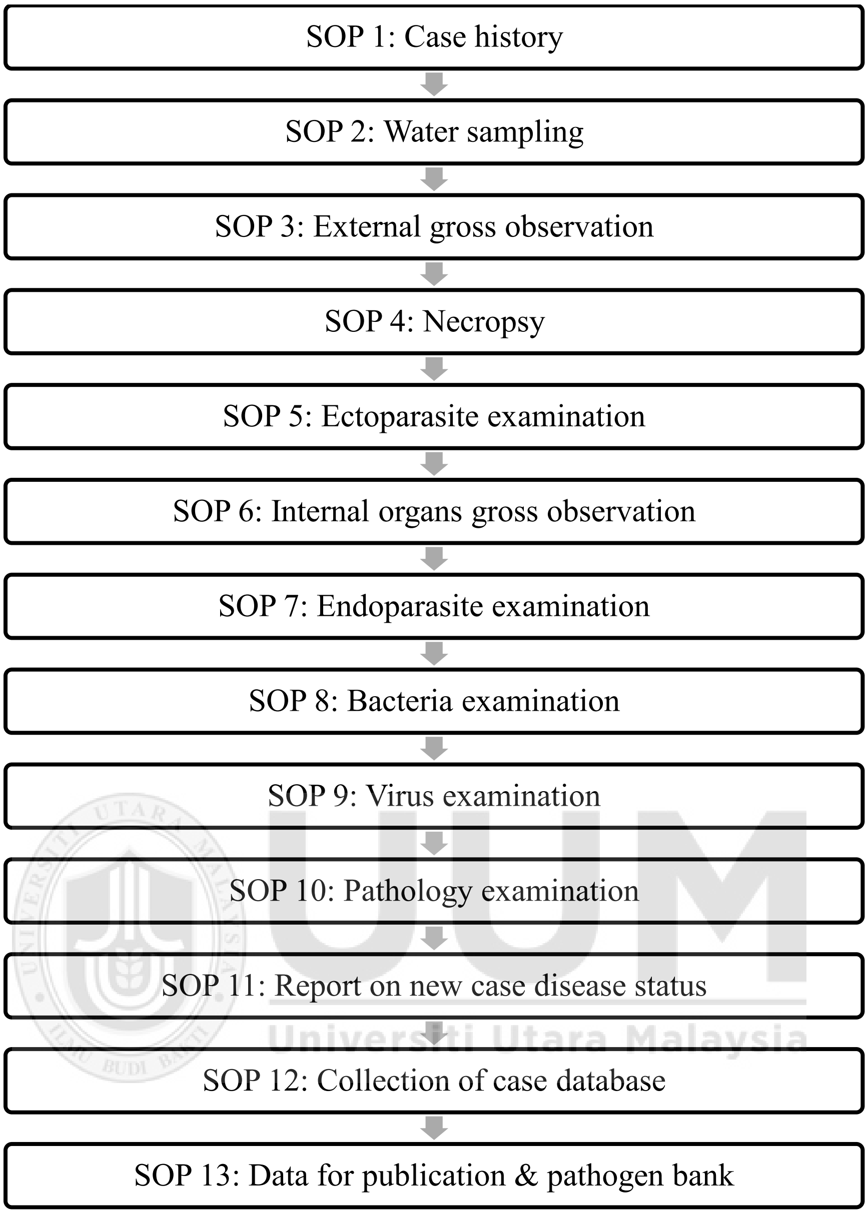


Figure 2.4: *Diagnosis Case Standard Operating Procedure (SOP)*
Reproduced from Kua et al. (2019)

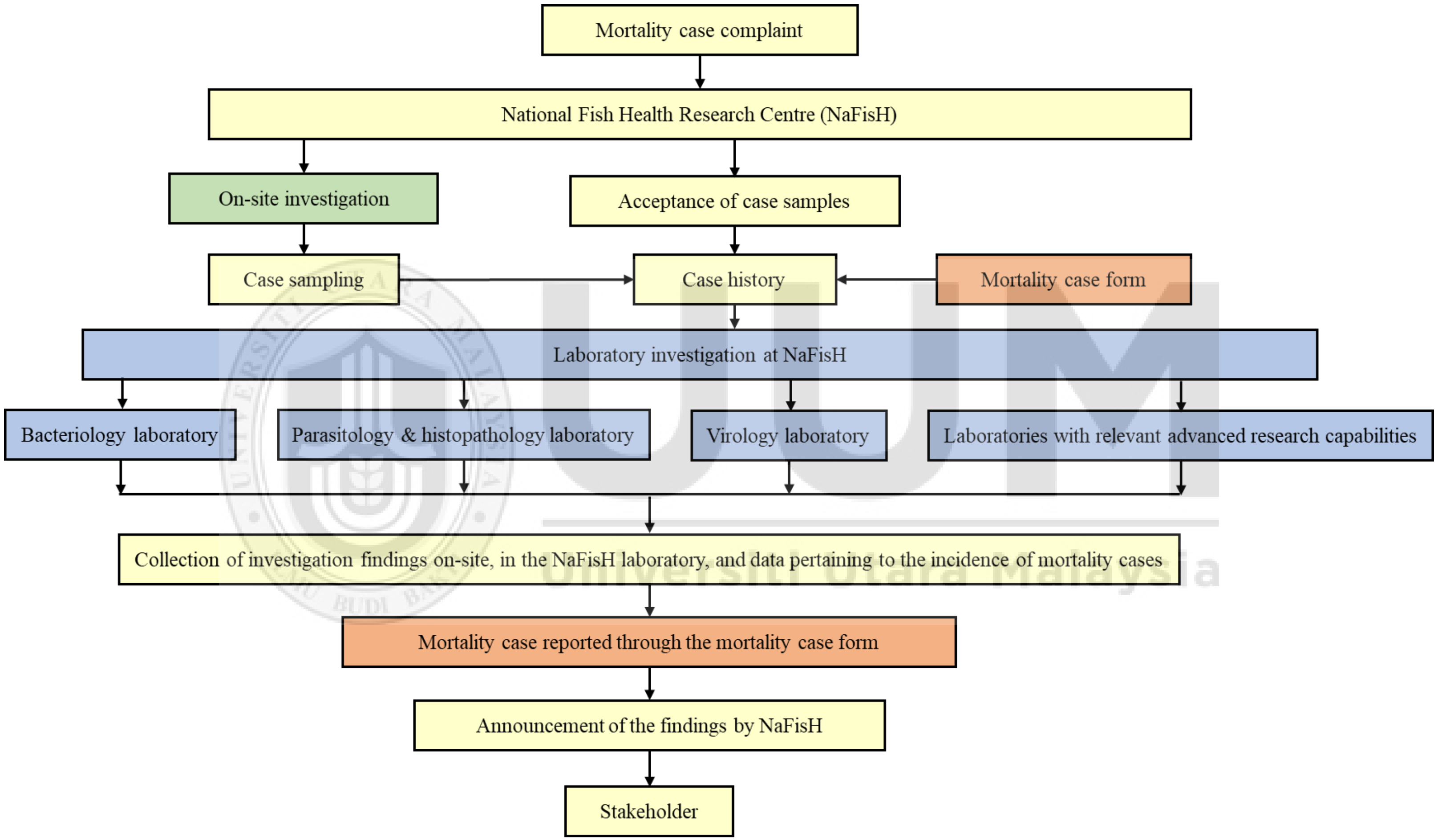


Figure 2.5: *Flow of Mortality Case Investigation by National Fish Health Research Centre (NaFisH)*
(Colour indication: yellow-whole investigation process, orange-discussion process, blue-laboratory investigation, green-on-site investigation)
Reproduced from Afzan Muntaziana et al. (2018)

Besides, this process requires prolonged and constant observation before a disease can be accurately identified, as highlighted by Adl & Younan (2019) and Darapaneni et al. (2022), making it time-consuming and labour-intensive. The accuracy of disease detection through human visualization is associated with the knowledge and experience of experts dedicated to studying each disease (Hitesh et al., 2015). It is also subjective and susceptible to bias and inconsistence which can influences the way diseases are classified as discussed by Muhammad Luqman et al. (2022) and Noraini et al. (2022). Moreover, the remote locations of fish farming sites present practical challenges for fish experts to access these areas in a timely manner for external gross observation during on-site investigation. As mentioned in studies by Hu et al. (2012), Li et al. (2002), and Nureize et al. (2007), the geographical distance and limited infrastructure can make it difficult for fish experts to physically reach remote fish farming sites promptly. As a result, the timely detection and treatment of fish diseases become impractical, potentially leading to delays in addressing problems.

In specific cases, this type of observation occurs within a laboratory environment, leading to a process that can be quite time-consuming. This process involves transferring the fish samples to a controlled laboratory setting, where fish experts can conduct the observation. However, this process is not only resource intensive but can also introduce delays in obtaining results due to the need for careful handling, preparation, and comprehensive analysis of the samples. While laboratory setting offers the advantage of controlled conditions, they come with the trade-off of extended time requirements, which can sometimes hinder swift decision-making or interventions, especially in cases where timely responses are crucial. Given the rapid transmission and potential devastation caused by fish diseases, it is imperative to prioritize early detection as a preventive measure. Effective monitoring, surveillance, and rapid process play a crucial role in detecting diseases at their earliest stages. Unfortunately, the early detection through external gross observation in standard procedure is perceived as tedious and time-consuming since it relies heavily on fish experts, which can pose limitations in terms of efficiency and real-time detection. Hence, it becomes crucial for the aquaculture industry to tackle this challenge by exploring new approaches to fish disease detection that offer detection capabilities independent of human observation.

2.3 Protozoan White Spot Disease

Parasitic diseases are often associated with more serious conditions that can lead to sustained production losses throughout the production cycle period (Gotesman et al., 2018). Among all the prevalent parasite species, *Ichthyophthirius multifiliis* protozoan or 'Ich' is capable of causing massive mortality, resulting in 100% in freshwater fish (Floyd & Reed, 2012; Gotesman et al., 2018). While *I. multifiliis* is confined to freshwater, another protozoan parasite, *C. irritans* is an obligate ectoparasite found in saltwater which has several features in common. *C. irritans* causes *cryptocaryonosis* often referred to as "protozoan white spot disease" or "marine ich" (Liu et al., 2020; Wright & Colorni, 2002). According to Chi et al. (2020), Huang et al. (2012) and Priya et al. (2012), *C. irritans* is the pathogen that causes protozoan white spot disease in a wide variety of marine fish species, including wild, ornamental, and cultured fish. Over the years, with the expansion of mariculture, protozoan white spot disease gradually disrupts mariculture, incurring heavy economic losses for fishermen worldwide (Colorni & Diamant, 1993; Hirazawa et al., 2001; Jiang et al., 2018).

Additionally, because of the parasite's rapid growth and the large population of fish in confined environments, like marine culture and aquariums, infection by this parasite has become a primary issue (Van & Nhinh, 2018). Moreover, because of the low degree of host specificity, it is capable of targeting most of the marine fishes (Yin et al., 2018), as well as freshwater species that have adapted to the saltwater environment (Burgess & Matthews, 1995). However, this disease damages the mariculture far more severely than aquarium fish (Cheung et al., 1979; Colorni, 1985; Dan et al., 2006). It is worse by the fact that *C. irritans* can destroy a whole farm in a short time (Cheng et al., 2020; Sun et al., 2006). Earlier work done by Chi et al. (2017) revealed that sporadic infections and outbreaks in intensive mariculture had been documented in numerous countries across the world, including the United States, South Africa, Australia, China, Japan, Korea, Taiwan, Thailand, Malaysia, and Israel due to broad host range (Xie et al., 2019; Yin et al., 2018). Meanwhile, most of the outbreaks in Malaysia happened during hatchery and nursery stages and it was found to infect marine hatchery and cage-culture of sea bass, grouper and snapper (Kua, 2008; Kua et al., 2001). Further, when fish fries are transferred to grow-out facilities, they are subjected to handling and transport stress (Nagasawa & Cruz-Lacierda, 2004). It became an unfavourable condition as these stressed fishes potentially carry the high intensity of *C. irritans*. Concerning these facts, it is noteworthy that *C. irritans* infections are very contagious and invariably fatal (Zuo et al., 2012). Since this disease can result in 100% mortality within a short period (Kua et al., 2001; Liu et al., 2020), this underscores the urgency and necessity of immediate action to prevent the outbreaks. In summary, the rapid detection and treatment of fish diseases are vital in preventing outbreaks and minimizing losses, particularly in the context of valuable cultured marine fishes in Malaysia.

2.3.1 Life Cycle Cryptocaryon Irritans

Initially, *C. irritans* was first discovered in marine fishes kept in aquariums and later was identified as a severe danger to marine culture fish (Watanabe et al., 2020). This single-celled protozoan parasite is found in wild and cultivated marine fish and poses a severe threat to mariculture due to broad transmission and host specificity (Cheng et al., 2020). The parasites are round to spherical, measuring approximately 0.3 to 0.5 mm, have cilia on the surface (Nagasawa & Cruz-Lacierda, 2004) and depends on live fish for survival (Cardoso et al., 2019; Floyd & Reed, 2012). Figure 2.6 illustrates *C. irritans* ciliate protozoan found on the yellowtail tangs' body surface (Cardoso et al., 2019).

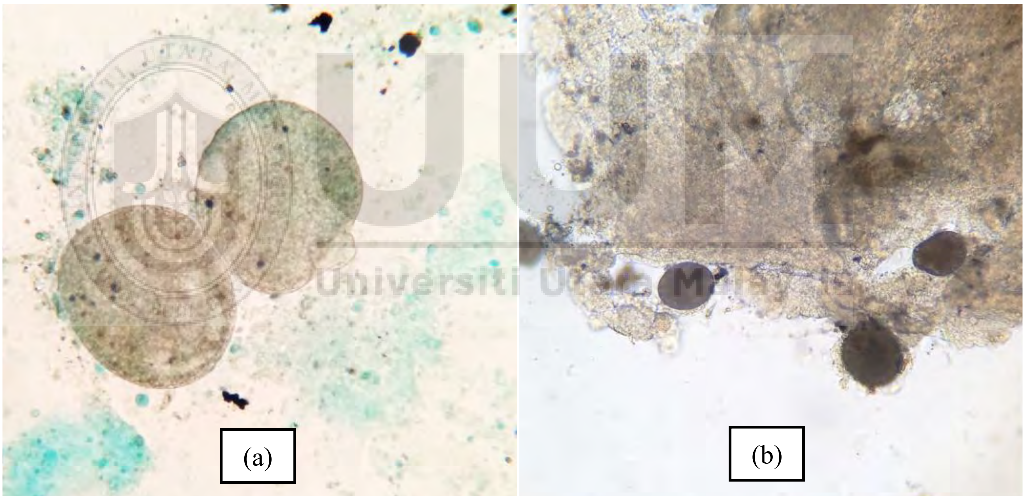


Figure 2.6: *Ciliated C. irritans at Microscopic Magnification (a): 10X and (b): 20X*
Source: Cardoso et al. (2019)

Furthermore, the parasite causing this disease has a life cycle (Yanong, 2017) which makes it different from other species of parasite, thus making the detection process at the early stage challenging. Parasite *C. irritans* go through a direct life cycle (Chi et al., 2020; Colorni & Burgess, 1997) consisting of four phases including feeding (*trophont*), off-host (protomont), reproductive (tomont), and free-swimming (theronts) (Khoo et al., 2012; Ma et al., 2016) as in Figure 2.7. Usually, the common noticeable stage is during the trophont stage where at this stage, the trophont is typically noticed rotating slowly underneath the skin (Van & Nhinh, 2018). Also, the common clinical signs, pinhead-sized whitish or grayish spots can be observed across the body surface and gills of the fish (Cardoso et al., 2019; Mo et al., 2016; Nagasawa & Cruz-Lacierda, 2004). The mature trophont then exits the fish and becomes a protomont prior to encysting stage (Yin et al., 2016) where during encysting stage, the tomont subdivides into numerous tomites via asymmetric binary fission (Chi et al., 2020). Subsequently, these tomites leave the cyst as theronts where they actively seek a new fish host and penetrate the tissue within 6 to 7 hours to start the next life cycle (Kua, 2014). Ultimately, the atmospheric temperature affects the *C. irritans*'s growth in which the optimum growth temperature ranges between 23°C and 30°C (Hirazawa et al., 2001; Van & Nhinh, 2018). Therefore, comprehending the life cycle of *C. irritans* is fundamental for studying and understanding the chronological incidence of the disease. This knowledge is crucial for the early detection and proper treatment of infected fishes, as it allows for timely interventions and effective disease management strategies.

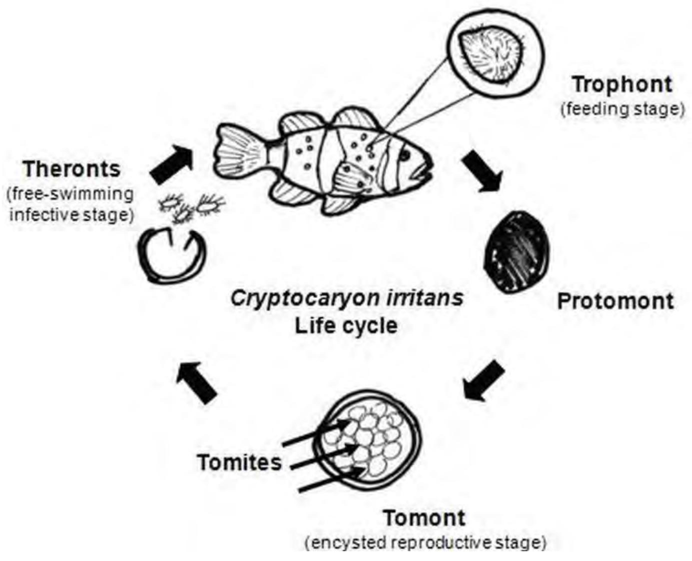


Figure 2.7: *Life Cycle of C. irritans*
Source: Ma et al. (2016)

2.3.2 Clinical Signs or Symptoms of Protozoan White Spot Disease

Based on Chen et al. (2008) and Xie et al. (2019), skin, gill and fins are the main targets of *C. irritans* during the infection, inhibiting the normal physiological function of fishes. The infected fishes usually show clinical signs such as pinhead-sized whitish or greyish spots, skin discoloration, excessive mucus production, loss of appetite, and respiratory difficulties (Cardoso et al., 2019; Colorni & Burgess, 1997). Figure 2.8 from Cardoso et al. (2019) illustrates the presence of white spots on infected yellowtail tangs (*Zebrasoma flavescens*) and greasy grouper (*Epinephelus tauvina*) in the study by Nagasawa & Cruz-Lacierda (2004). In addition to visual signs, infected fish may display abnormal swimming behaviour such as rubbing against objects or exhibiting fin tremors, likely due to itchiness. Kua (2014) suggests that high infection in the eyes can lead to bruising caused by rubbing against objects. In severe cases, infected fish may become lethargic, linger near the water surface, exhibit cloudy corneas, and display ragged fins. Simultaneously, the gills are often pale with a generous amount of mucus. Skin erosion can lead to the formation of ulcers, which are prone to secondary infections. Notably, the white spots may be challenging to visualize on light-coloured species, such as seabass, with the eye, as mentioned by Cardoso et al. (2019) which could lead to late detection of protozoan white spot disease thus result in a large number of infected fish within a period of time. Hence, having a robust knowledge of the morphological features is indispensable in the development of a new procedure for white-spot disease detection using underwater images.

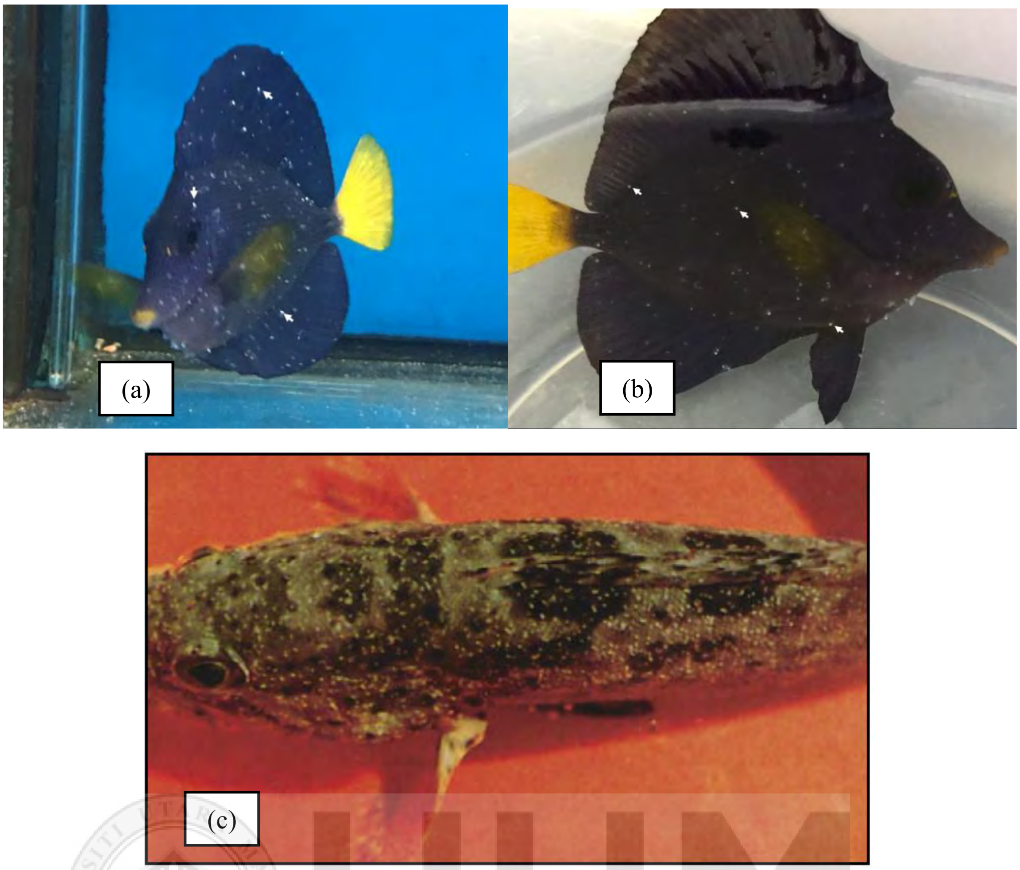


Figure 2.8: *White spots on (a) & (b): Yellowtail tang; (c): Greasy grouper*
Source: Cardoso et al. (2019); Nagasawa & Cruz-Lacierda (2004)

2.4 Computer-Aided Approach in Fish Disease Detection

The concept of utilizing automation within agriculture industry is not novel and its adoption is increasingly prevalent. However, the technical hurdles linked with automation can greatly differ based on the specific circumstances. While certain straightforward automated systems, have been effectively in use for some time, others require a higher level of complexity to be viable. This complexity is notably evident when it comes to automated disease diagnosis, especially concerning fish diseases. The rapid and precise detection of diseases holds immense significance for adeptly managing problems, whether when dealing with humans, animals, or plants. The most effective approach to achieve this entails the presence of a specialized expert who can assess the situation and suggest suitable actions. Nonetheless, this is not always achievable, particularly in remote locations. This challenge is especially prominent in the case of fish farming, given that these operations are frequently situated far from government agencies.

In addressing this issue, three technological approaches based on computer-aided can be employed, each leveraging technological tools that differ in the levels of automation (Barbedo, 2014). Table 2.1 summarize the differences in computer-aided technological approaches in fish disease detection (Barbedo, 2014). The goal is to strike a balance between accuracy, timeliness, and cost-effectiveness, ensuring that disease detection and management remain effective, even in remote or challenging environments. Consequently, this study is focused on utilizing the image-based automatic approach as the computer-aided approach by rooting in the fact that this approach does not hinge on human intervention, endowing it with a high degree of automation and speed.

Table 2.1: *Summary of Computer-Aided Technological Approaches in Fish Disease Detection*

Technological approach	Description	Degree of automation	Advantages	Limitation
Remote diagnosis system	• Operates by connecting experts with on-site individual remotely, experts provide diagnosis and recommendations based on the information provided	Low automation	Offers a personal touch with experts	• Relies heavily on human interaction and expertise • Time-consuming
Expert system	• Aim to replicate the decision-making abilities of human experts • Users typically respond to a series of questions related to disease symptoms and the system generate a diagnosis based on the gathered information	Semi automation	More cost-effective to maintain compared to remote diagnosis system	• Accuracy depends on the inference engine, logical and knowledge base • Relies on inputs from non-expert users to generate a diagnosis, incorrect inputs can lead to inaccurate outputs
Image-based automatic system	• Utilize advanced AI • Based on colour and morphological features extracted from images of disease symptoms to deduce the presence of a disease	High automation	Real-time diagnosis	• Achieving high level of reliability poses substantial challenges

Reproduced from Barbedo (2014)

2.5 Underwater Imaging

The utilization of underwater research is dependent on the captured underwater images' quality. Acknowledging the properties of light propagation is crucial as a fundamental requirement for underwater study to gain a valuable understanding on the actual conditions of the underwater environment. Figure 2.9, as depicted by Zhang et al. (2021a), illustrates the conditions and challenges associated with underwater imaging. Understanding these properties of light propagation is essential for effectively conducting research and obtaining reliable insights from underwater images.

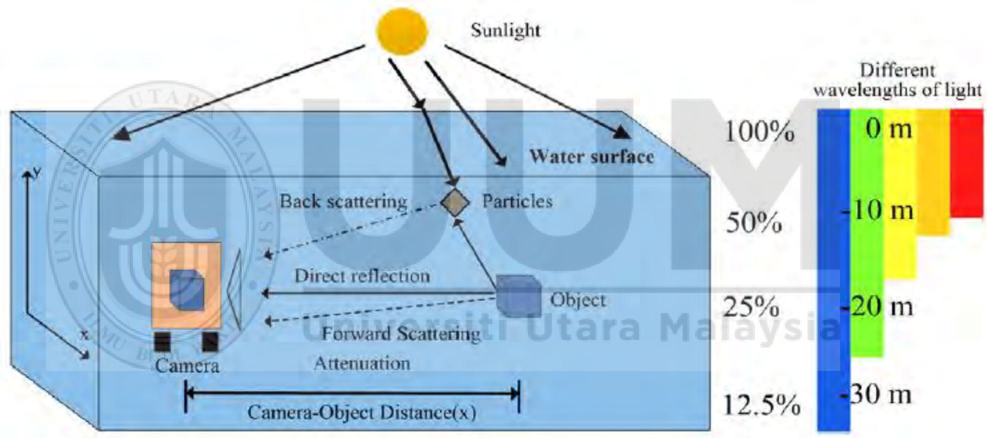


Figure 2.9: *Illustration of Underwater Imaging*
Source: Zhang et al. (2021a)

Underwater imaging is significantly affected by the properties of water, which influence the characteristics of light. As light travels from its source to the object and then to the imaging device, it interacts with water and impurities, leading to degradation in the quality of the captured images. Compared to images taken in air, the degradation problem of underwater images is considerably different due to the significantly higher density of water, which is approximately 800 times denser than air air (Karthiga & Ashokraj, 2013; Wong et al., 2021). Occasionally, the degradation of underwater image's quality is associated with underwater imaging light, called as light attenuation (Almutiry et al., 2021; Li et al., 2020; Moghimi & Mohanna, 2021; Natarajan, 2017; Prasath & Kumanan, 2020). Light attenuation is a sum of absorption; loss of light energy as it traverses through the medium and scattering; changes in the light's path. Light is attenuated at an exponential rate as it traverses through the water at different wavelengths resulting in poor contrast and hazing (Raveendran et al., 2021; Schettini & Corchs, 2010; Wong et al., 2021; Zhang et al., 2020).

Water serves as a natural light absorber, absorbing a meaningful amount of light, leading to difficulty in obtaining clear and satisfactory underwater images, as noted by Soni & Kumare (2020). The properties of the water medium result in the differential absorption of light based on its wavelength, as shorter wavelengths of light are more readily absorbed by water, while longer wavelengths can penetrate deeper. Since the green and blue colours have a longer wavelength, both travel the furthest, causing underwater images to be entirely influenced by green and blue (Zhang et al., 2019). Due to this selective absorption, underwater images often exhibit a greenish or bluish tint, as discussed in studies by Prasath & Kumanan (2020) and Suharyanto et al. (2021). As a result of this phenomenon, the vibrancy and fidelity of the captured images is significantly reduced.

Meanwhile, scattering is divided into forward scattering and backward scattering. For further explanation, in forward scattering, light reflected from the targeted object is scattered in various directions, leading to blurriness in images (Raveendran et al., 2021; Song & Wang, 2021). Conversely, in the case of backward scattering, the light is reflected by the floating particles before it is able to reach the targeted object (Liu et al., 2019; Zhang et al., 2019). The appearance of floating particles such as 'marine snow' (sand and minerals) and micro phytoplankton, further contributes to unwanted noise and haze as highlighted by Li et al. (2016), and Schettini and Corchs (2010). A recent study by Li et al. (2020) indicated that these suspended particles also limit the visibility, reduce the contrast, and even diminish the colours, affecting the overall quality and clarity of underwater images. As a result of absorptive and dispersion nature of light in the water, it is challenging to obtain pleasant images.

To compensate for the limited penetration of sunlight at greater depths, underwater photographers often utilize artificial light sources to enhance visibility and illuminate the scene, as mentioned in studies by Jaffe (2010), Sethi and Indu (2020), and Wang et al. (2019). Unfortunately, just a fraction of light reaches the camera, and the rest is scattered as it travels through the water medium. Uneven lighting scenes can be particularly problematic, as reflections and masks caused by uneven lighting can obscure image details and create a central flash spot with poor lighting in the surrounding areas, as observed by Galdran et al. (2015), Muñoz et al. (2023) and Yang et al. (2019). Furthermore, during a sunny day, the flickering effects appear and cause strong highlights in the captured image (Lu et al., 2016, 2017). These effects can further impact image quality and visibility in underwater photography. In short, the underwater images interested in this study can be agonized by one or more of these major issues: low contrast, low visibility, haze, colour distortion (bluish appearance) and uneven lighting. Therefore, these challenges related to underwater images need to be tackled to obtain clear underwater images for accurate observation of the underwater analysis.

2.6 Underwater Image Enhancement

In past decades, numerous research efforts have been undertaken to unveil sophisticated and effective underwater image processing aimed to overcome the limitations inherent in underwater imaging. This action is extremely vital to fulfil the requirements for underwater studies, including remote sensing applications and underwater object detection. Plus, understanding and making a rational conclusion of the real-life underwater scenario is only possible if clear underwater images are obtained (Zhang et al., 2021b). Hence, due to the complicated underwater environment, enhancing process is considered as a challenging task. Underwater image enhancement is a technique used to selectively spot the region of interest (ROI) or conceal the non-ROI by modifying the intensity levels, resulting in a clearer output image than the original underwater image, in which it is used to visualize better some of the features based on the actual aim (Yang et al., 2020). This involves adjusting contrast and grayscale, eliminating noise, sharpening object features like edges, and correcting colour. Furthermore, image processing offers a wide range of underwater image enhancement techniques and commonly used techniques include histogram equalization, white balancing, fusion based, dark channel prior (DCP) and colour correction (Soni & Kumare, 2020). Summary of studies using various image enhancement techniques is summarized in Table 2.2.

Blurring and haze are among the major challenges of underwater images, akin to issues encountered in foggy imagery. Underwater dehazing technique utilizing DCP was inspired by the work of by He et al. (2011) that aims to remove fog in the outdoor images. The main concept underlining this algorithm is that at least one channel in the RGB colour channel contains pixels whose intensity is so low that it is almost zero (Chang et al., 2018). According to Drews et al. (2017), these low intensities are due to shadows, coloured objects or surfaces having at least one colour channel with low intensity, such as fish, algae, or coral, and dark objects or surfaces, such as rocks or dark sediment. Several researchers reported on the use of DCP (Ashwin et al., 2017; Gu et al., 2016; Hou et al., 2019; Li et al., 2016; Pati et al., 2018; Xie et al., 2018) to remove haze from a single input underwater image. Yet, there are some drawbacks in the DCP, including darkening local regions of the image, low contrast of the background region (Ashwin et al., 2017), and ineffective in removing blurring in the regions that are much brighter (Pramunendar et al., 2018). Plus, the result of the underwater image dealing with the DCP algorithm alone is still not ideal.

Due to the disappearing of colours in an underwater image, sophisticated techniques are proposed to recover the colours and contrast that have been absorbed by the water. The technique often used to improve contrast is the contrast limited adaptive histogram equalization (CLAHE) algorithm of Rayleigh distribution. Comparing to histogram equalization (HE), CLAHE improves the contrast and at the same time, equalizes the image histogram (Pramunendar et al., 2018). This is because problems related to noise amplification that arise when using HE can be avoided by using CLAHE (Hassan et al., 2020; Muhammad Suzuri et al., 2013; Sharma et al., 2019; Suharyanto et al., 2021; Wan Nural Jawahir et al., 2013). In the case where CLAHE was applied on the RGB model alone, it produces new artifact colours from the original images. While, when CLAHE was applied on the HSV model, the image turns to be brighter than the original image and looks unnatural as well as causing the presence of noises in certain regions. Hence, these problems were solved by Muhammad Suzuri et al. (2013) by using the CLAHE algorithm on combined RGB and HSV models resulted in enhanced contrast, providing a natural-looking underwater image while decreasing undesirable artifacts. Besides, this traditional algorithm for contrast enhancement is easily utilized and capable of enhancing the edges of objects thus enhancing overall features in the image. However, this technique can also generate excessive noise and unable to adapt to varying distances of the captured images. The recent research by Suharyanto et al.

(2021) proposed on the use of CLAHE to increase the quantity of matching images using SURF and the average optimization result obtained is 76.8%.

Ashwin et al. (2017) considered solution to overcome the limitation in DCP by integrating DCP with CLAHE algorithms for better underwater image quality. Besides, they also further applied CC algorithm to produce a more visually pleasing image. It was concluded that the proposed method is more favourable than the DCP and CLAHE alone. In addition, to make up for the trade-off in the DCP approach, colour correction also sometimes generates a lot of noise (Pramunendar et al., 2018). A different approach was taken by Li et al. (2016) to overcome problems related to DCP by adopting the luminance adjustment strategy after obtaining the dehazed images. This strategy was incorporated to equalize the non-uniform illumination and at the same time, preserve image particulars.

Oppositely, Pramunendar et al. (2013) following the work made by Norsila et al. (2012), uncovers a solution to the issue of images that require more contrast but have a variety of colour shades. They employed the automatic level colour correction (ALCC) algorithm to automatically adjust the image's lighting, thereby increasing the number of matching images with SIFT. Still, it only results in 4% increment of the performance of SIFT image matching. In 2018, Pramunendar et al. considered a contrast-adaptive colour correction (CACC) to counter the drawback from the previous study by enhancing underwater images without adding noise. As a result, underwater image quality is enhanced without diminishing the quality or over-improving it. A year later, the authors studied the impact of CACC technique on accuracy comprehensively. According to the findings, accuracy increased from 4.68% to 93.73% and kappa measures went from 0.05 to 0.92 respectively for fish species identification. This improvement happened because the features of fishes in the image were more distinguishable with the enhanced quality image.

Ancuti et al. (2018) took a different approach, combining colour balance and multi-scale image fusion. Using underwater light scattering as a source of colour cast, the white balancing process intended to remove the colour cast, while the multi-scale implementation of the fusion process produced an artifact-free blend. The degradation of colour fading, contrast reduction, and detail blurring problems can be solved using more advanced and comprehensive underwater picture improvement approaches, as an example, Zhang et al. (2021b) employed a CC and Bi-interval contrast enhancement algorithms. Without considering underwater image attenuation compensation, Fu et al. (2017) and Zhang et al. (2021a) applied the piece-wise stretching procedure for colour correction. Despite their impressive successes, the proposed method is difficult to implement and demands the use of additional colour models like CIELAB, which limits its practical usefulness.

After all, the majority of the previous research only targeting on solving one or two of the problems in underwater images (Wang et al., 2020). Gu et al. (2016) and Li et al. (2016) focus solving the haze problem, and Muhammad Suzuri et al. (2013) focus on the problem of colour and contrast in the image. Plus, some of the existing research have neglected the noise problem produced by the algorithms (Pati et al., 2018). Thus, existing approaches must be improved so that noise can be reduced or eliminated from the output images. According to Pramunendar et al. (2019), many researchers were not focusing much on the impact towards the performance of the classification method. Majority only intended to enhance the images to be used for feature extraction in which the relationship between improved image towards classification performance is not comprehensively studied. This is crucial to determine the adaptability of the technique with classification. Therefore, it is important to study on image enhancement technique that is able to overcome problems in underwater images; and at the same time can help in improving the performance of classification methods or when applied to unlimited amount of data. So far, the best method found was proposed by Pramunendar et al. (2019) using CACC since it is proven to enhance underwater images moderately in terms of visibility, brightness, contrast, and noise, and help to improve the accuracy in the classification method.

Table 2.2: *Summary of Underwater Image Enhancement Techniques*

Authors	Techniques	Datasets	Results	Advantages & Disadvantages
Song & Wang (2021)	Multi-scale fusion & global stretching of dual model (MFGS)	Underwater Image Enhancement Benchmark (UIEB) dataset	Addresses a wide range of distortion scenarios in underwater images	Advantage: - Improves contrast and correcting colour deviation Disadvantage: - Lacking in terms of colour richness of the resulting images and the execution time
Suharyanto et al. (2021)	CLAHE	Underwater images are taken from Central Java, Indonesia using Olympus Tough-8010 camera	Enhances the quality of underwater images	Advantages: - Optimizes underwater image matching results using SURF method
Zhang et al. (2021a)	Colour correction & Adaptive contrast enhancement	UIEB dataset	Outperforms the second-best by at least 5% in the average of all metric scores	Advantages: - Applicable for the subsequent feature extraction process - Improves haze and low-light images Disadvantage: - Over-enhanced areas for images captured under artificial light
Zhang et al. (2021b)	Colour correction & Bi-interval contrast enhancement	UIEB dataset	Achieves similar or better performance compared to ARC, UDCP, IBLA, GDCP, FB, HB and TS	Advantages: - Enhances visibility and contrast in both coloured and non-coloured low-light images - Achieves a natural appearance with improved visibility and clearer details Disadvantage: - Poor results when dealing with significant noise
Zhang et al. (2020)	Colour correction & Dehazing	- U45 dataset - Real-world underwater image enhancement (RUIE) dataset	- Outstanding results compared to CLAHE, DCP, MSRCR, and FB	Advantages: - Effectiveness and practicality in feature extraction

Table 2.2 (Continued)

Bai et al. (2020)	Global & local equalization of histogram & Dual-image multi-scale fusion (GLHDF)	UIEB dataset	Obtains similar or higher values compared to UIBLA, GDCP	Advantage: - Satisfactory results in various conditions of underwater images captured Disadvantage: - May increase the computational complexity of GLHDF
Wang et al. (2020)	Multiple methods: Combination of bilateral filter, DCP, white balance & CLAHE	Underwater images of setup experiment taken using Go Pro	Enhances colour, contrast, and more detail	Advantage: - Adaptability to various turbidity levels
Kamil Zakwan et al. (2019)	Natural-based underwater image colour enhancement (NUCE)	UIEB dataset	High average entropy, gradient and PCQI	Advantages: - Enhance various underwater scenes with high visibility - Significantly reduce underwater colour cast
Pramunendar et al. (2019)	Contrast-adaptive colour correction technique (CACC)	Fish4Knowlege image dataset obtained from LifeCLEF 2014 (LCF-14)	Better accuracy and kappa measurements compared to DCP, ALCC, CLAHE, AWB, DCP-ALCC, DCP-CLAHE, DCP-AWB	Advantage: - Improve classification accuracy performance
Guraksin et al. (2019)	Wavelet transforms & Differential evolution algorithm	- Images captured from Antalya city in Turkey - Images taken from publication	Better entropy and PSNR	Advantage: - Visual information is more distinguishable

Table 2.2 (Continued)

Pramunendar et al. (2018)	Contrast-adaptive colour-correction (CACC)	Fish4Knowlege dataset	- Yields PSNR value 4.4% higher than the highest value obtained by DCP, ALCC, CLAHE, AWB, DCP-ALCC, DCP-CLAHE, DCP-AWB	Advantages: - Not excessively improve quality images
Ahamed et al. (2018)	Slide stretching	Underwater images taken from internet sources	Produces better results compare to HE, AHE, CLAHE	Disadvantage: - Limited reliable evaluation metrics
Zhang et al. (2018)	Multi-scale fusion strategy	UIEB dataset	Obtains better visual quality of underwater images	Advantage: - Reduces the execution time
Ancuti et al. (2018)	Colour balance and Multi-scale image fusion	- Images taken by seven different professional cameras - UIEB dataset	Better exposure of the dark regions, improved global contrast, and edges sharpness	Advantage: - Improves the accuracy of image segmentation
Ashwin et al. (2017)	Integrated models: Combination of DCP, CLAHE & colour correction	Underwater image (source not mentioned)	Favourable outcome	Advantage: - Helps in monitoring the underwater scenario
Fu et al. (2017)	Colour correction & novel optimal contrast improvement method	UIEB dataset	Excellent results compared to other methods	Advantages: - Suitable for real-time applications

Table 2.2 (Continued)

Li et al. (2016)	DCP and Luminance Adjustment	UIEB dataset	Performs better than DCP and improved Retinex model	Advantages: - Improves global contrast of the image
Gu et al. (2016)	DCP	Underwater image (source not mentioned)	Reduces blur	Advantage: - Contributes to accurately classify fish
Pramunendar et al. (2013)	Automatic Level Colour Correction (ALCC)	Underwater images taken from Karimunjawa Island, Central Java, Indonesia	4% increment in SIFT performance	Advantages: - Overcomes the problem of time-consuming during clipping Disadvantages: - Not significantly improve image matching
Muhammad Suzuri et al. (2013)	CLAHE	Underwater images taken from Redang Island and Bidong Island, Terengganu, Malaysia	Improves the visual quality of underwater images by enhancing contrast, as well as reducing noise and artifacts	Advantages: - Useful for a wide range of underwater images applications Disadvantages: - Cannot adapt with varying distances of the captured images

2.7 Artificial Intelligence (AI) in Fish Disease Detection

The automation principles that underlie AI's success in aquaculture and other domains have fuelled its rapid growth (Jha et al., 2019; Sukhadia et al., 2020). Massive developments in computer science open the room for the development of AI (Hashimoto et al., 2018). Furthermore, AI enables tasks to be accomplished quickly and with minimal human involvement. It has emerged as a multidisciplinary field within computer science, encompassing various subfields such as Machine Learning (ML), natural language processing (NLP), knowledge-based systems, computer vision, planning, optimization, and robotics (Abioye et al., 2021) as depicted in Figure 2.10. In past years, there has been a growing focus on AI applications in fish disease detection, which are discussed in this section.

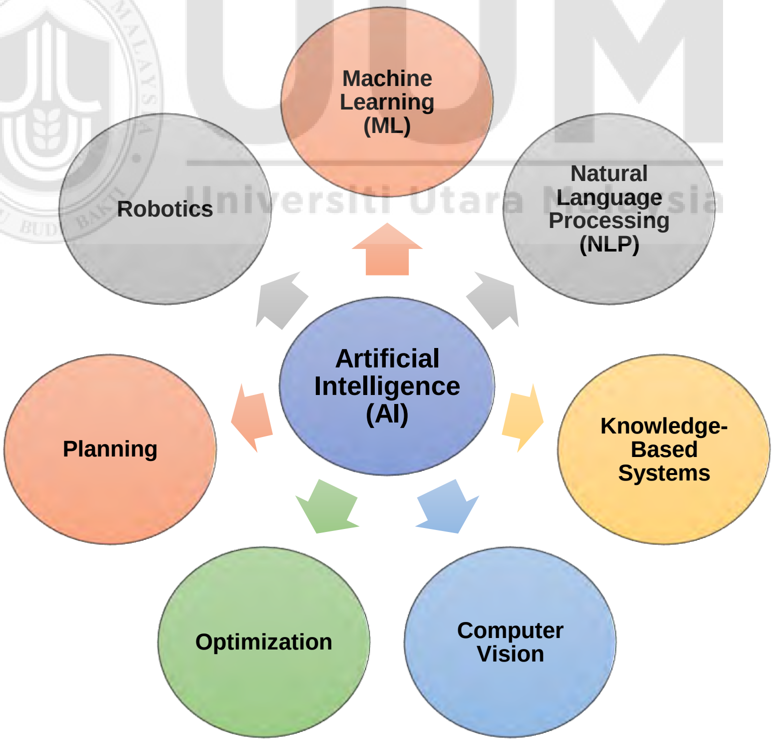


Figure 2.10: *Subfields of AI*
Adapted from Abioye et al. (2021)

2.7.1 Deep Learning

ML has revolutionized various fields and has found applications in diverse domains, such for the case of fish images, the ML technique has been developed and used to monitor the growth, condition, and species of fish that is not limited to disease detection using numerous algorithms. Numerous ML algorithms have been utilized in fish-related studies, such as fish species classification (Allken et al., 2018; Hu et al., 2016; Li & Hong, 2014; Pramunendar et al., 2019), fish counting (Aliyu et al., 2017; Le & Xu, 2017; Lumauag, 2018; Marini et al., 2015; Spampinato et al., 2008), and fish disease (Adl & Younan, 2019; Ahmed et al., 2021; Hitesh, 2019; Hu et al., 2016; Sikder et al., 2021). Nevertheless, within ML, a domain expert is typically required to identify and extract most of the intricate features of the subject being studied. This is done to reduce data complexity and make patterns more discernible for effective learning (Saleh et al., 2022). In contrast, machine learning allows for training on smaller datasets, but it necessitates greater human intervention to facilitate learning and rectify errors (Taye, 2023). Determining those features for a specific task can be challenging and time-consuming (Min et al., 2017). Another limitation of ML approaches is their tendency to overfit quickly as the size of the training dataset increases (Ghojogh & Crowley, 2019; Taigman et al., 2014; Ying, 2019). This issue restricts the extent to which the application can be deployed. To overcome these limitations, researchers have turned to deep learning (DL) as a breakthrough in ML.

Revolutionary technology was raised as DL, a subset of ML that gained increasing interest due to outstanding performances that dominate in various application areas (Khanna, 2019; Yang et al., 2020). Indeed, DL stands out due to its capacity to learn directly from raw and unstructured data, enabling superior analysis for processing massive volumes of data. Figure 2.11 provides a performance comparison between DL and ML models, considering the volume of data which demonstrates that DL models, when trained on larger datasets, exhibit improved performance (Sarker, 2021). As noted by Muhammad Luqman et al. (2022), DL is known for its low input variability and minimal pre-processing requirements. This capability has great potential in the context of smart fishing, as DL algorithms can uncover, quantify, and interpret large and diverse datasets to aid in fisheries management (Ebrahimi et al., 2021). Thus, DL can address challenges associated with limited intelligence and poor performance when studying large-scale, multisource, and diverse big data sets in aquaculture.

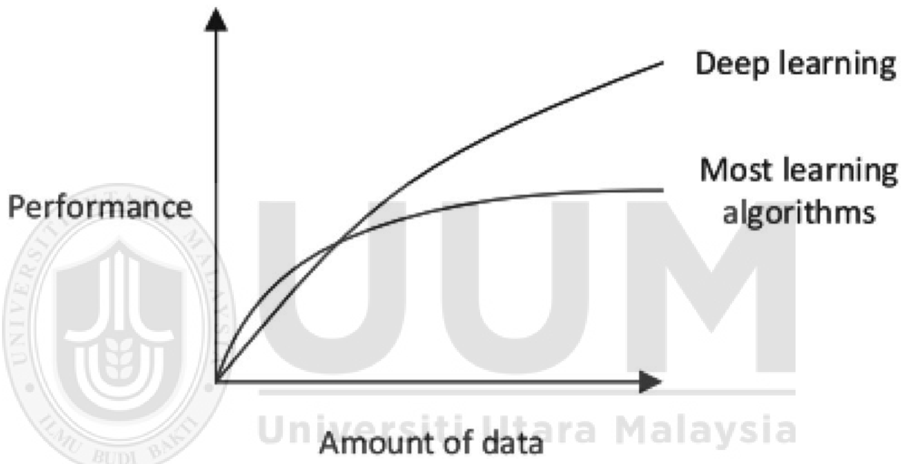


Figure 2.11: *DL vs ML Modelling in View of Data Sizing*
Source: Sarker (2021)

Both convolutional neural networks (CNN) and recurrent neural networks (RNN) are widely utilized DL models. CNN, drawing inspiration from the human visual nervous system, particularly excels in tasks related to image detection and classification (Cui et al., 2020; French et al., 2020; S. Liu & Deng, 2016; Rathi et al., 2018; Rauf et al., 2019), whereas an RNN performs exceptionally well in the serial data processing. It has demonstrated exceptional performance in various studies related to image analysis. According to Yamashita et al. (2018), CNN architecture consists of input and output layers, as well as hidden layers containing convolution, rectified linear unit (ReLU), pooling, and fully connected layers. Convolution and pooling layers perform feature extraction, while the fully connected layer transforms the extracted information into the final output. Figure 2.12 depicts an example of a CNN architecture used for fish detection task (Saleh et al., 2022). Additionally, large dataset and the wide range of environmental variations captured in the datasets contribute to assessing the robustness and performance of the trained models. The interpretability of DL models can be challenging, making it difficult to understand their decision-making process. Nevertheless, with the continuous advancements in DL and the availability of large datasets, this approach holds great promise for solving increasingly complex problems in various domains.

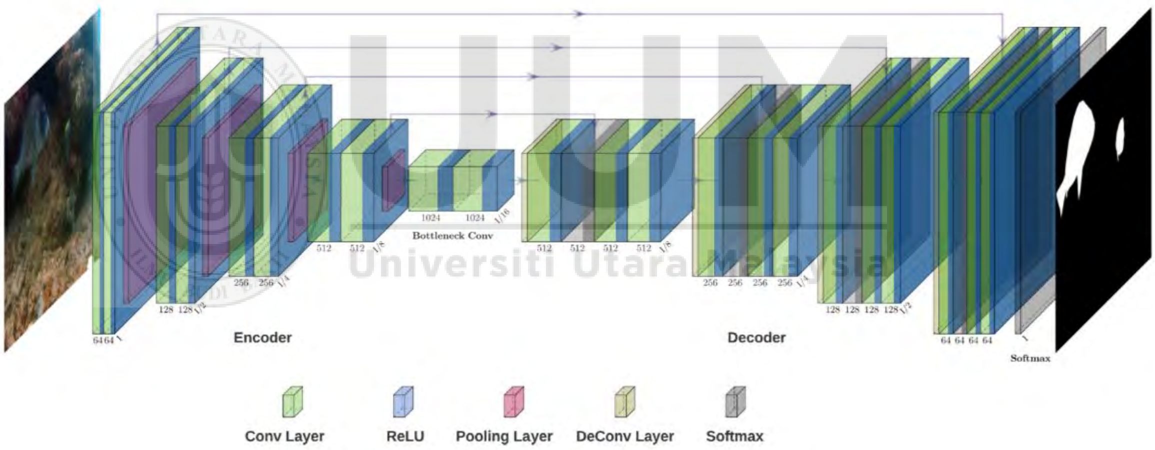


Figure 2.12: *Example Architecture of a CNN for Fish Detection Task*
Source: Saleh et al. (2022)

2.7.2 Application of AI in Fish Disease Detection

For detecting fish diseases, numerous models are using a variety of factors, for example including explanations of visible external symptoms and signs, behavioural signals, water quality, and images of sick fish or microscopic images (Barbedo, 2014). Several AI methods with numerous classification techniques including ML and DL have been developed in the subject of fish disease detection. Summary of eighteen (18) studies in fish disease detection is listed in Table 2.3 in the year chronology. A significant difference observed in the research landscape for fish species classification and recognition as compared to fish disease detection. While a multitude of studies have used underwater images as a dataset for developing models in the former domain, there is limited research exploring the use of these images for fish disease detection. To bolster the reliability and robustness of these methods, it becomes imperative to conduct additional research that delves into the actual underwater scenarios. This will not only help bridge the existing gap but also provide an overview of underwater conditions, which is crucial for effective fish disease detection. Furthermore, there has been a notable absence of studies for the detection of protozoan white spot disease *cryptocaryonosis* employing AI method.

Based on previous literature searches, the early application of the AI method is based on rule-based expert systems. Despite the good performance, expert systems are still prone to mistakes during the detection process, even if the irregularities and distortions are minor. Knowledge gained through rule-based approaches can be readily translated into simple programming rules, yet this approach's performance is dependent on the knowledge and abilities of the experts, and this knowledge can be compromised by errors. In contrast, there is less control over the decision-making process when using case-reasoning rules, which are drawn from previously solved cases. This rule-based approach necessitates the system to undergo extensive training with a substantial number of cases, which in turn consumes a significant amount of time. Furthermore, to keep the system at the forefront of its performance when deployed in real-world applications, it requires ongoing long-term maintenance and support. In contrast, when dealing with advanced and automated technologies like ML and DL, rule-based expert systems face practical limitations due to their inherent drawbacks. These limitations can make rule-based approaches less favourable for applications that demand adaptability, scalability, and the ability to handle complex, unstructured data efficiently.

The majority of research efforts have primarily focused on classification using ML techniques. Prior to the classification, manually designed feature extraction methods, such as HOG, SIFT, GH, GLCM, and FAST have been used to extract relevant features from the images. These feature extractors have exhibited impressive performance on specific tasks (Alsmadi & Almarashdeh, 2020; Hu et al., 2016; Malik et al., 2017b; Spampinato et al., 2008; Storbeck & Daan, 2001). Despite the efficient performance, these techniques have fallen short of expectations, largely because they are manually designed low-level features that extract features such as texture, shape, and colour of an image. These techniques necessitate domain knowledge from experts, and most of the time cannot be reused to new datasets (Bengio et al., 2013; O' Mahony et al., 2019; Taye, 2023). Furthermore, these techniques often display decreased robustness when dealing with images characterized by either low-contrast or high-contrast conditions.(Khai et al., 2022; Nanni et al., 2017).

Meanwhile, ML techniques proposed for instance, SVM (Huang et al. 2015; Siddiqui et al., 2018), LR (Adl & Younan, 2019), KNN (Malik et al., 2017a) and PNN (Divinely et al., 2019) are notably influenced by the size and quality of the training dataset which collectively impact the final classification accuracy in many cases (Ying, 2019). Within the domain of ML, the effectiveness heavily depends on the successful extraction of well-defined features from the data (Janiesch et al., 2021). This necessitates careful curation of the training data and human expertise in feature engineering and error correction (Ghojogh & Crowley, 2019; Taye, 2023). The choice and quality of features play a crucial role in the accuracy and generalization ability of

ML. Appropriate feature extraction enables the ML to capture relevant patterns and information from the data, leading to better predictions and insights. Moreover, it is worth noting that overfitting is a challenge inherent to supervised ML (Taigman et al., 2014; Ying, 2019). As outlined by Ghojogh and Crowley (2019), overfitting arises when a model is trained excessively, causing it to exhibit high variance in its estimations and low bias.

Conversely, DL offer distinct advantages over other techniques, as underscored by prior studies due to its swiftness, high degree of automation, and remarkable performance. Within DL, CNN stands out because it eliminates the necessity for manual feature extraction. Instead, CNN autonomously learns features from the data as they are trained on a set of images. This inherent ability makes DL exceptionally accurate for image classification tasks. Furthermore, CNN is capable of learning feature detection across multiple hidden layers, with each layer augmenting the complexity of the acquired features. A noteworthy recent study conducted by Gupta et al. (2022) in this domain has achieved remarkable results by employing CNN as a DL algorithm. The attained accuracy surpassing 96.7% serves as a benchmark for future investigations. However, it is imperative to note that the adoption of DL in AI model development is dependent on a factor: the availability of large and comprehensive dataset. In conclusion, there exists a pressing need to propose a more robust method that employs underwater image dataset to enhance the precision of fish disease detection.

Table 2.3: *Application of AI in Fish Disease Detection*

Authors	Dataset	Method	Results	Advantages/ Disadvantages
Lou et al. (2007)	- Images collected from farming log records	- Pre-processing: De-noising, smoothing, image enhancement, edge detection and image binarization - Segmentation: Histogram-based - Feature Extraction: Statistical feature, Xiong-based wavelet method, SIFT - Classification: SVM	- Not mentioned	Advantages: - Improve performance of expert system Disadvantage: - Time-consuming to establish a database
Park et al. (2007)	- Images collected from different aquaculture farms in Wando, Jindo and Yosu areas of Korea - 60 parasites microscopic images from the internet, printed materials	- Pre-processing: 3×3 mean, edge sharpening filters, levelling, edge detection masks & binarization - Object Detection: Morphological erosion and dilation operations - Feature Extraction: Polar coordinate & geometrical feature - Classification: PCA & correlation coefficient	- Correct detection performance: 90% - Average correct recognition rate: 86%	Advantages: - Offers greater convenience, consistency, and speed when compared to manual Disadvantage: - Limited dataset
Han et al. (2011)	- Online: Parasite microscopic images collected from the internet, hard copy materials, and digital images - Images from user input in Wando, Jindo, and Yeosu areas of Korea	- Pre-processing: 3×3 mean, edge sharpening filters, levelling, edge detection masks & binarization - Object Detection: Morphological erosion and dilation operations - Feature Extraction: Polar coordinate & geometrical feature - Classification: PCA & correlation coefficient	- Not mentioned	Advantages: - Provides easy and rapid detection of diseased olive flounder Disadvantage: - Time-consuming to establish database - Complex and requires high maintenance
Hitesh et al. (2015)	- EUS infected fish images collected from Valley, Assam taken using SLR camera	- Segmentation: PCA, K-means clustering - Feature Extraction: HSV & morphological operations open - Classification: Euclidian distance	- Accuracy: >90%	Advantage: - Improve disease detection with greater precision - Correctly compute the diseased area Disadvantage: - Limited dataset

Table 2.3 (Continued)

Lyubchenko et al. (2016)	- Images from public internet access	- Segmentation: Colour image segmentation - Classification: Based on colour markers	- Successful detect infected areas on the fish body and identified a total area of lesions	Advantages: - Offers the flexibility to adjust the marker size when selecting colours during image segmentation, preventing the appearance of false data points Disadvantages: - The process of individually marking objects are time-intensive and not very efficient
Hu et al. (2016)	- Live infected fish images received from farmers	- Pre-processing: 3×3 media filter - Feature Extraction: GH, GLCM, mean of the R, G, B, RGB, H, S, I and HSI component - Classification: Multi-SVM	- Successful designs a recognition system for infected fish species	Advantage: - The combination of colour and texture features prove to be more effective than relying solely on any single type of feature Disadvantage: - Limited dataset
Malik et al. (2017a)	- Images taken from NGRF, Lucknow and CIFRI, Kolkata	- Pre-processing: Morphological operations & Canny's Edge Detection - Segmentation: - Feature Extraction: HOG or FAST, PCA - Classification: NN or K-NN	- Accuracy: (HOG-PCA-KNN): 56.32%, (FAST-PCA-KNN): 63.32% (HOG-PCA-NN): 65.8% (FAST-PCA-NN): 86%	Advantage: - Fast and efficient method compared to manual Disadvantage: - Limited dataset
Hitesh (2019)	- Infected EUS fish images collected from Hailakandi, Assam	- Segmentation & Feature Extraction: HSV space component	- Segmentation method accurately segment the diseased portion	Advantage: - Overcome issue spot identification of disease fish Disadvantage: - Only used feature extractor

Table 2.3 (Continued)

Adl & Younan (2019)	- Microscopic images collected from multiple media sources and engines	- Pre-processing: Gaussian filter & GrabCut - Feature Extraction: ORB - Classification: LR Classifier - Optimization: ACO	- Accuracy: 92.8% - Precision: 0.94 - Recall: 0.93 - F1 Score: 0.93	Advantage: - Enhances classification performance while utilizing fewer extracted data features Disadvantage: - Limited dataset
Divinely et al. (2019)	- Images taken from various internet resources	- Pre-processing: Noise filter & morphological operations - Feature Extraction: CWT & GLCM - Classification: PNN	- Accuracy: >90% - Specificity: 100% - Sensitivity: 50%	Advantage: - PNN minimizes probability of misclassification Disadvantage: - Limited dataset
Jhansi et al. (2019)	- Images extracted from underwater video taken using waterproof video camera attached at the bottom of the ship	- Pre-processing: UKF - Feature Extraction: GLCM - Classification: ENN by Back Propagation Algorithm (BPA)	- Efficiency: 98%	Advantage: - Enhances classification performance Disadvantage: - EBP algorithm has low convergence and poor generalization
Waleed et al. (2019)	- Images from different internet resources - Extracted images from underwater video taken using GoPro camera	- Pre-processing: Conversion to different colour space - Segmentation: Gaussian distribution - Classification: CNN	Accuracy: 99.0446% (Alexnet architecture)	Advantage: - Testing on different CNN architectures Disadvantage: - Rely on segmentation process
Ahmed et al. (2021)	- Images collected from internet - Images acquired from aquaculture firms	- Pre-processing: Cubic spline interpolation & AHE - Segmentation: K-means clustering - Feature Extraction: Statistical & GLCM - Classification: SVM	- Accuracy: 94.12% - Precision: 89.06% - Recall/Sensitivity: 90.48% - Specificity: 95.57% - F1 score: 89.76% - False positive rate: 9.52% - False negative rate: 7.14%	Advantage: - Low number of misclassifications Disadvantage: - Limited dataset

Table 2.3 (Continued)

Sikder et al. (2021)	- Images collected from Kaptai reservoir and fishery Ghat in Rangamati and Sunamganj Haor areas of Bangladesh	- Pre-processing: Noise filtering & Contrast stretching - Segmentation: K-means & C-means clustering - Feature Extraction: GLCM & Gabor filter - Classification: SVM	- Accuracy: 96.48% (K-means) & 97.90% (C-means)	Advantage: - Testing on two different clustering methods - Various types of fish Disadvantage: - Not underwater images
Noraini et al. (2022)	- Source of images not enclosed	- Classification: CNN	- Accuracy: 94.44% - Sensitivity: 88.89% - Specificity: 94.44%	Advantage: - No preprocessing is necessary Disadvantage: - Limited dataset
Muhammad Luqman et al. (2022)	- Images collected from aquaculture farms in Kedah, Malaysia	- Pre-processing: Data augmentation (resizing & rotation) - Classification: Region-based CNN (R-CNN)	- Mean average precision (mAP) with 0.237	Advantage: - Resnet V2 (proposed) resulted in highest value of mAP and AR compared to Backbone of VGG19 and ResNet152 Disadvantage: - Not underwater images
Gupta et al. (2022)	- Underwater images captured at Norwegian Institute of Marine Research (IMR), Bergen, Norway	- Pre-processing: Data augmentation (resizing & rotation) - Image Enhancement: CLAHE - Classification: CNN	- Accuracy: 96.7%	Advantage: - Underwater images Disadvantage: - Unable to locate the wound or lice on the fish
Mia et al. (2022)	- Images captured using digital camera collected locally from the fish market and fisheries	- Pre-processing: Resizing & colour space conversion - Image Enhancement: HE - Segmentation: K-means clustering - Feature Extraction: Statistical & GLCM - Classification: RF, Gradient Boosting, BPN, CPN, KNN, SVM, K-Star, Logistic Regression	- Accuracy: 88.87% (Random Forest)	Advantage: - Testing on different ML algorithms Disadvantage: - Limited dataset

2.8 Performance Evaluation

Many studies employ performance evaluation metrics like accuracy and precision for fish recognition and classification (Qin et al., 2016; Siddiqui et al., 2018). Similarly, in the context of fish disease detection, various performance evaluation metrices are utilized, with accuracy being the most common as in Table 2.4. To evaluate a classification model's capacity to make accurate predictions on a specific data, a confusion matrix (CM) is usually employed. The confusion matrix comprises four key components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) (Ahmed et al., 2021). TP and TN correspond to condition where predictions are accurate, either positive or negative, respectively. Conversely, FP represents positively false predictions, and FN signifies negative predictions that turned out to be incorrect. The confusion matrix offers a transparent and comprehensive means of assessing a model's performance, enabling researchers to understand the reliability of algorithms in the specified task.

Table 2.4: *Performance Evaluation Indexes for Fish Disease Detection*

Evaluation index	Description & Formula	References
Accuracy	The proportion of specifically classified infected fishes and the total number of fishes in the test set $$\frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100$$	Adl & Younan (2019) Ahmed et al (2021) Hitesh (2019) Mia et al. (2022) Noraini et al. (2022) Waleed et al. (2019)
Precision	The ratio of correctly classified infected fishes (TP) and the ground truth (the sum of TP and FP) $$\frac{TP}{(TP+FP)} \times 100$$	Adl & Younan (2019) Ahmed et al (2021)
Recall/ Sensitivity	The ratio of classified infected fishes (TP) from the ground truth (total number of TP and FN) $$\frac{TP}{(TP+FN)} \times 100$$	Adl & Younan (2019) Ahmed et al (2021) Divinely et al. (2019) Noraini et al. (2022)

Table 2.4 (Continued)

Specificity	The ratio of TN and the summation of FP and TN $\frac{TN}{(FP+TN)} \times 100$	Adl & Younan (2019) Ahmed et al (2021) Noraini et al. (2022)

The primary goal of developing an automated procedure is to alleviate the manual workload of humans by offering a faster and more accurate alternative. Beyond technical considerations, evaluating the performance of the automated procedure extends to a more comprehensive assessment that serves as a pivotal means of enhancing its functionality. Consequently, it becomes imperative to assess the procedure's performance not only in terms of accuracy but also in terms of expert assessment, particularly when compared to the existing standard procedures employed by humans. The use of expert assessment has become a primary method for supporting the scientific and technical developments in many fields, serves as a valuable tool in the decision-making process (Marinchenko, 2020). This holistic evaluation process not only ensures that the automated procedure meets or exceeds the benchmarks set by human operators but also gathers feedback and insights from experts within the relevant domain field.

The use of surveys plays a crucial role in obtaining these insights, allowing experts to provide their opinions on a range of categories and enabling data-driven decisions for continual improvement. This approach underscores the importance of designing the procedure with the expert at the centre, facilitating quantitative analysis, and providing an efficient and cost-effective means of collecting valuable feedback. To gather this feedback effectively, a set of survey questionnaires can be employed, using a Likert scale to enable experts to express their opinions and preferences across various dimensions (Nemoto & Beglar, 2014). The Likert scale has been a widely accepted and convenient tool for collecting participants' preferences and gauging their level of agreement with a set of statements (Heo et al., 2022). It allows for the construction and customization of responses, yielding valuable data that can be used for statistical analysis and inference. Ultimately, experts' feedback could add credibility and provides valuable perspectives that contribute significantly to the overall evaluation of the developed procedure.

2.9 Summary

The findings from this literature review reveal the process of fish disease detection is considered an onerous task that demands solutions for reliable detection particularly considering the fish experts and their experiences. Undoubtedly, the pursuit of early fish disease detection through novel approaches emerges as a critical concern for the mariculture industry as it can offers an alternative to the standard procedure of external gross observation. However, it is imperative to acknowledge that the current state of disease detection using AI method remains imperfect, primarily due to the limitations posed by poor underwater image quality. In an effort to address challenges associated with the underwater environment, numerous researchers have explored various image enhancement techniques tailored specifically for underwater images. However, the majority of image enhancement research has been primarily focused on enhancing the visual quality of underwater images for feature extraction purposes, without delving into the subsequent impact on the classification process for objects affected by underwater environmental factors. Consequently, the adaptability of image enhancement techniques with classification methods remains relatively unclear. Hence, there is a crucial need for research that delves into comprehensive and effective image enhancement techniques capable of simultaneously addressing issues like colour distortion, poor contrast, noise, and haze in underwater images while also enhancing the performance of classification. In this context, the study aims to build upon the work conducted by Pramunendar et al. (2019), which employed the CACC as an image enhancement technique due to its ability to moderately improve the quality of underwater images afflicted by low visibility, low brightness, noise, and low contrast, while also enhancing the accuracy of classification.

The primary distinction lies in the predominant use of underwater images for fish species classification and recognition in previous studies, with only a limited focus on employing these images for fish disease detection. Furthermore, prior to the integration of AI methods, there was a scarcity of research addressing the detection of protozoan white spot disease *cryptocaryonosis* in mariculture fish. While earlier studies employed AI method for fish disease detection, they predominantly relied on rule-based expert systems. However, these rule-based systems are limited by their dependence on expert knowledge and can be susceptible to errors. As a result, the current trend in technology has shifted towards more advanced and automated approaches, particularly machine learning (ML) and deep learning (DL) techniques, to enhance fish disease detection.

ML techniques have shown efficiency, but they fall short due to reliance on the successful extraction of well-defined features from the data. Achieving successful results in this context requires meticulous curation of the training data and the application of human expertise in feature engineering and error correction. In contrast, DL technique, particularly CNN has demonstrated their speed, automation, and performance advantages. CNN automatically learns to extract relevant features from images during training, eliminating the need for manual feature extraction. CNN-based classification models consistently outperform ML models and are inherently robust to certain transformations and variations in the input data, such as translations, rotations, and overlapping. So far, the most notable contribution in the realm of fish disease detection using CNN has been the study conducted by Gupta et al. (2022), which yielded significant results. Nevertheless, there is an imperative need for the development of a more robust approach that leverages underwater images to achieve a more precise and meticulous detection of fish diseases.

CHAPTER 3

METHODOLOGY

3.1 Overview of the Chapter

This chapter serves as a vital component of the study, as it outlines the methodology used to detect protozoan white spot disease. The overview of the entire study is presented in Section 3.2. Subsequently, Section 3.3 delves into the detailed process of acquiring underwater fish images, while Section 3.4 focuses on the identification of morphological features. The detection of protozoan white spot disease is covered in Section 3.5, where a new procedure is developed, integrating image enhancement and classification techniques. Furthermore, Section 3.6 comprehensively discusses the performance evaluation of the proposed procedure. The chapter concludes with a summary, offering conclusive remarks and insights derived from the contents presented in this chapter.

3.2 Study Framework

The primary approach employed in this study is an experimental one, comprising five distinct phases designed to fulfil the research objectives including initial investigation and research proposal preparation, image acquisition, morphological features identification, procedure design and development, and performance evaluation. Figure 3.1 represents an overview of the study plan illustrating the activities associated with each phase's objectives. During the first phase, research interest and gap areas were identified based on the literature review and consultation with the fish experts. This initial investigation lays the foundation for the research experiment. Moving on to the second phase, the underwater fish images were acquired from the experimental setup conducted at the National Fish Health Research (NaFisH) in Batu Maung, Pulau

Pinang. In the subsequent phase, morphological features protozoan white spot disease was identified from the collected underwater images. In the fourth phase, the new procedure for detecting protozoan white spot disease was implemented. This procedure entails image enhancement using CACC followed by classification using CNN. Finally, in the fifth phase, the performance of the new procedure was evaluated to assess its accuracy and effectiveness.

The main contribution of this study lies in the development of the new procedure for detecting protozoan white spot disease using AI method based on underwater images. This procedure, which integrates CACC and CNN, offers a novel approach compared to the external gross observation in the standard procedure. Additionally, a novel dataset was generated through the experiment conducted, further enriching the study. Figure 3.2 depicts the framework of the overall processes involved in this study. The following sections explore into each phase in more extensive detail.

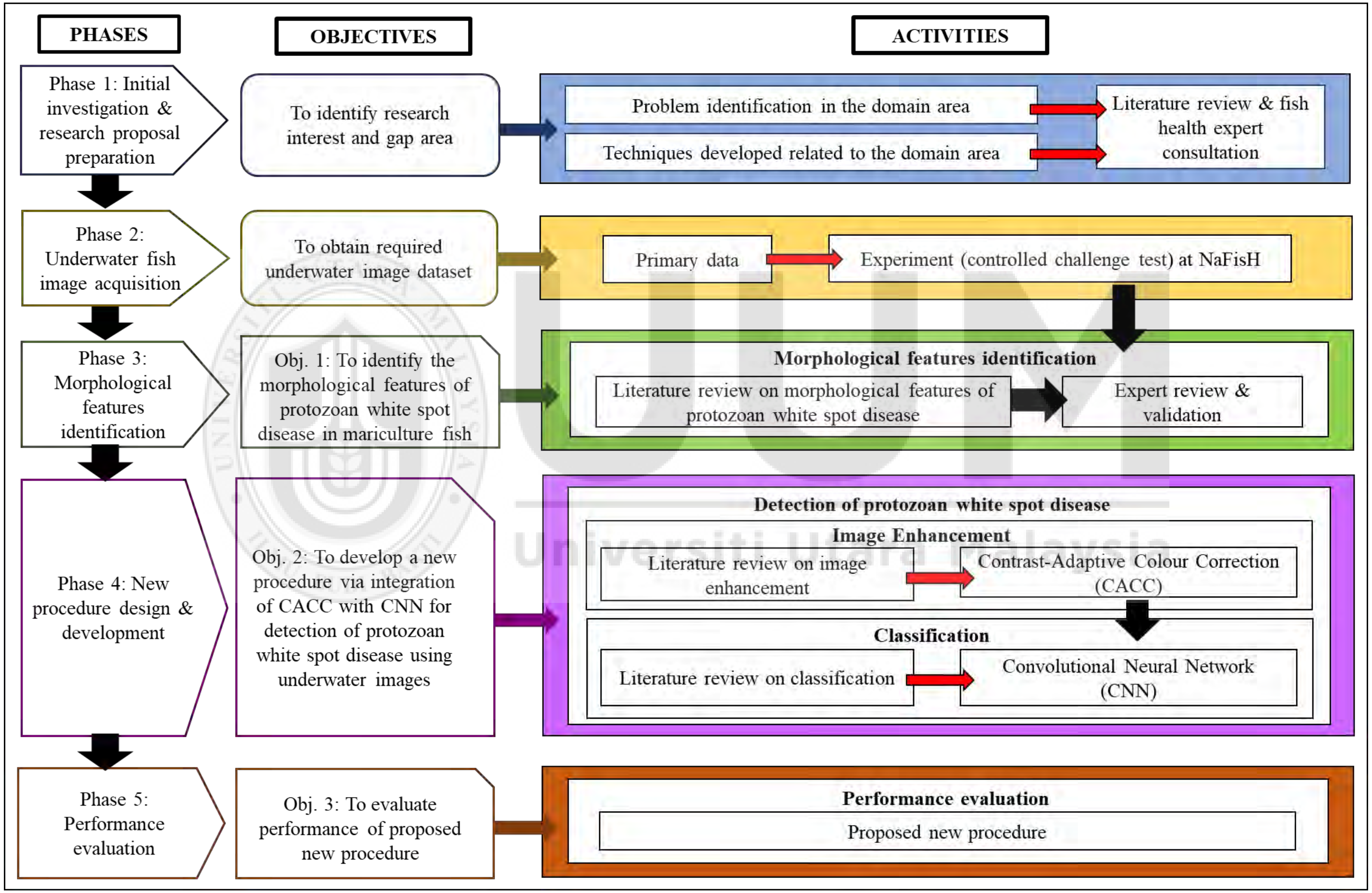


Figure 3.1: *Overview of the Study Plan*

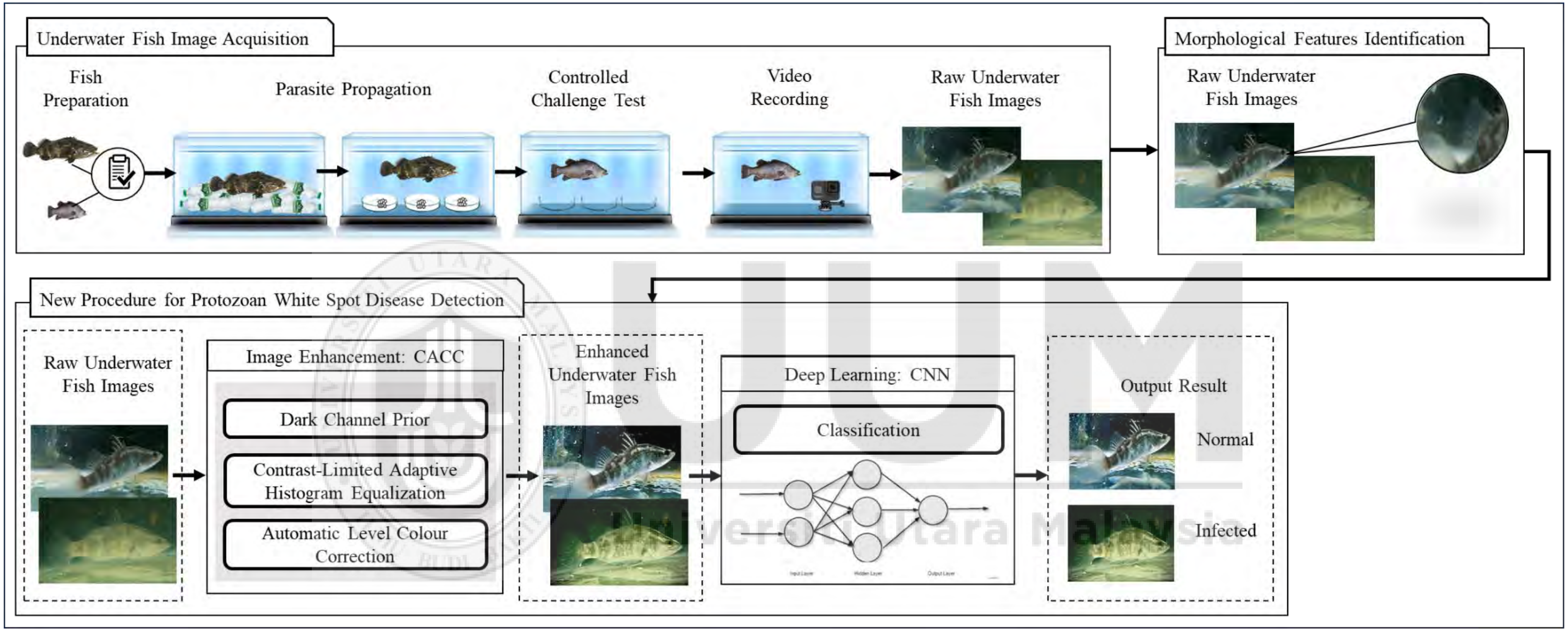


Figure 3.2: *Framework for the Overall Processes of the Study*

3.3 Underwater Fish Image Acquisition

Image acquisition is a critical initial step in image processing as a process of retrieving images. In this study, the underwater fish images utilized for training the CNN algorithm was obtained from the experiment conducted at the National Fish Health Research (NaFisH) in Batu Maung, Pulau Pinang. The images acquired through this process were in their raw, unprocessed form and categorized as primary data. The procedure for acquiring the images was thoroughly explained in the subsequent subsections. The experimental study focused on using seabass fish since this species is the top-produced mariculture fish in Malaysia, making it a relevant choice for this study. The experimental setup involved utilizing a GoPro camera positioned in the fish tank environment, as illustrated in Figure 3.3. This setup enabled the capturing of underwater fish images in their natural habitat, allowing for a close representation of actual environment to be gathered for analysis and training purposes.

Figure 3.3: *Experimental Setup of the GoPro Camera*

3.3.1 Procedure for Underwater Fish Image Acquisition

Since a publicly accessible underwater image dataset of protozoan white spot infected fish was not available, this study took the initiative to create a new dataset. The underwater images were captured during a controlled challenge test, which involved conducting experiments with fish (seabass) and the parasite *C. irritans*. To prepare the dataset, the parasite *C. irritans* was first propagated in grouper fish to obtain a sufficient amount of the parasite. The collected *C. irritans* at the tomonts stage were then incubated until they developed into theronts. These theronts were used in the controlled challenge test with the seabass fish. During the controlled challenge test, images of both normal and protozoan white spot infected fish were captured. This process ensured that the dataset contained a diverse range of images representing both healthy fish and those affected by the protozoan white spot disease. The overall overview of the procedure for image acquisition is shown in Figure 3.4, highlighting the steps involved in preparation of the new dataset for further analysis and experimentation in this study.

<u>Materials and Methods:</u>

Fish Preparation

Three (3) groupers (4 ± 0.5 kg) and fifty (50) juvenile seabass (8-13 cm in length) were obtained from Nibong Tebal, Pulau Pinang and Sungai Petani, Kedah. The collected seabasses were placed in a 1-tonne tank equipped with an aeration system (acting as a holding tank), subjected to saltwater-adaptation for two weeks prior to the controlled challenge test. To ensure the health of the batch, ten (10) seabass were subjected to disease screening tests, verifying their freedom from parasite *C. irritans* and other diseases. Daily monitoring of the fish was conducted throughout this period.

Parasite propagation

For the propagation of parasites, each grouper was individually placed in a 150-L aquarium tank equipped with an aeration system. To induce stress and prompt the development of white spots, a sudden temperature change was applied using ice blocks. This process was repeated daily until the appearance of white spots on the fish's body. Once these spots emerged, petri dishes were positioned at the tank bottom to collect tomonts detached from the fish. After two days of white spot appearance, numerous tomonts (cysts) adhering inside the petri dishes were gathered.

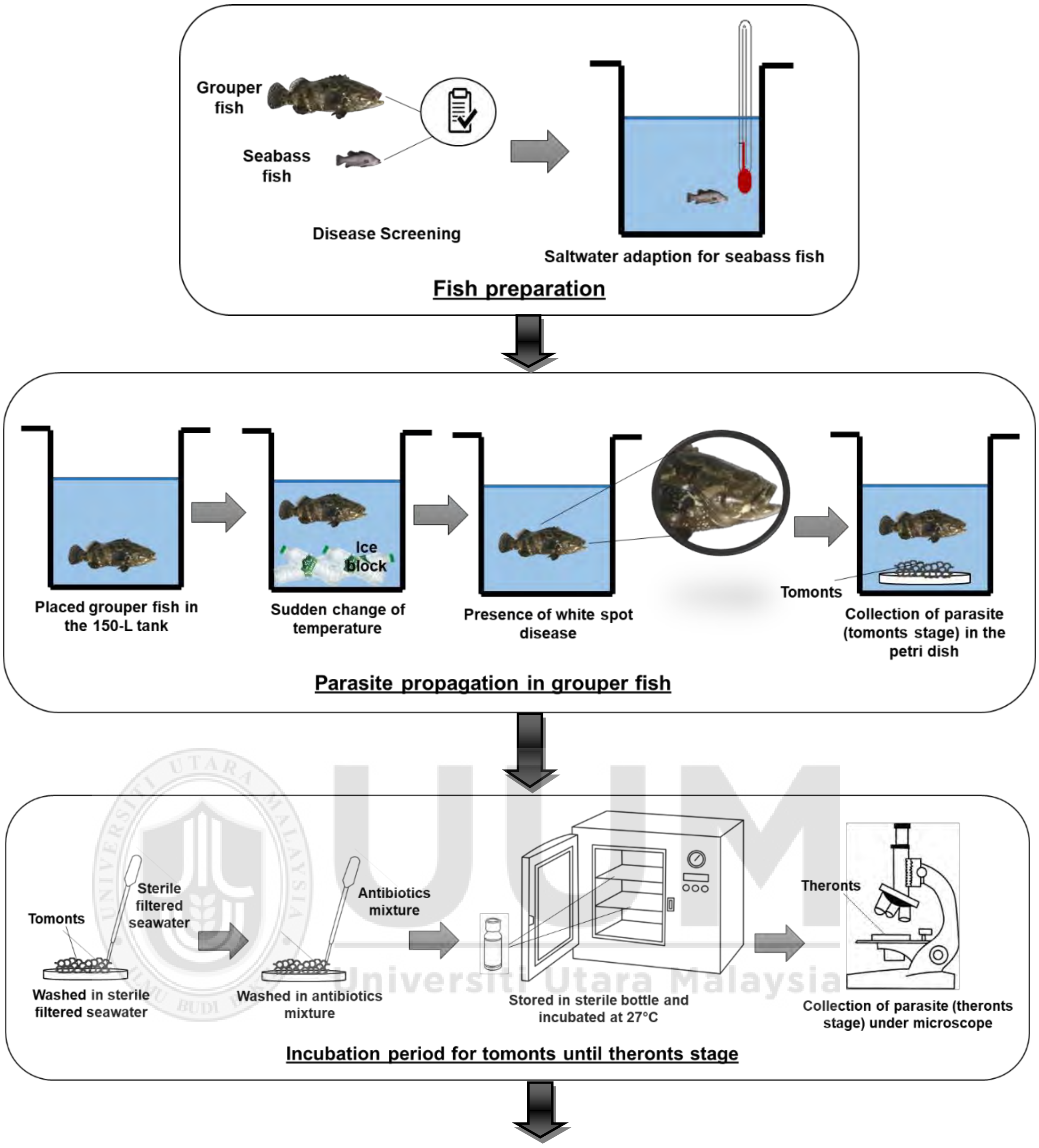
Note: If there was no occurrence of protozoan white spot disease within one week, a grouper from a different source was substituted.

Incubation period for tomonts until theronts stage

The tomonts collected underwent a series of washes in sterile filtered seawater to eliminate host debris and to dilute the bacterial flora. Tomonts were subjected to three further washes in 10 mL of the appropriate antibiotic mixture containing 1% penicillin and streptomycin. Maintaining sterile conditions, tomonts were transferred to 5mL filtered seawater in a sterile bottle (8mL) and incubated at 27 °C. Encysted tomonts may showed signs of division were then allowed to complete its division in fresh solution of filtered sea water without antibiotics. The release of theronts were transferred by micropipette (5 µl) into a 24-well plate under a dissecting microscope and calculated. The theronts were collected and to be used in a controlled challenge test.

Parasite in controlled challenge test

Twenty-four (24) individual seabass were placed in separate 24-L aquarium tanks, each equipped with an aeration system and labelled either as challenge/infected or control/normal. Of these, twelve (12) replicates were subjected to a parasite *C. irritans* challenge, while the other twelve (12) served as the control group without any challenge. Two hundred (200) theronts were introduced into each 24L tank labelled as challenge/infected. Throughout the challenge test, videos were recorded alternately for each challenged seabass using a GoPro Hero 9 Black camera over a three-hour period during daylight for 3 consecutive days. Simultaneously, videos of each seabass in the control/normal group, not challenge with the parasite, were recorded in alternation using the same camera setup over the subsequent 3 days.


Grouper fish
Seabass fish
Disease Screening
Saltwater adaption for seabass fish
Fish preparation
Placed grouper fish in the 150-L tank
Ice block
Sudden change of temperature
Presence of white spot disease
Tomonts
Collection of parasite (tomonts stage) in the petri dish
Parasite propagation in grouper fish
Tomonts
Sterile filtered seawater
Washed in sterile filtered seawater
Antibiotics mixture
Washed in antibiotics mixture
Stored in sterile bottle and incubated at 27°C
Theronts
Collection of parasite (theronts stage) under microscope
Incubation period for tomonts until theronts stage

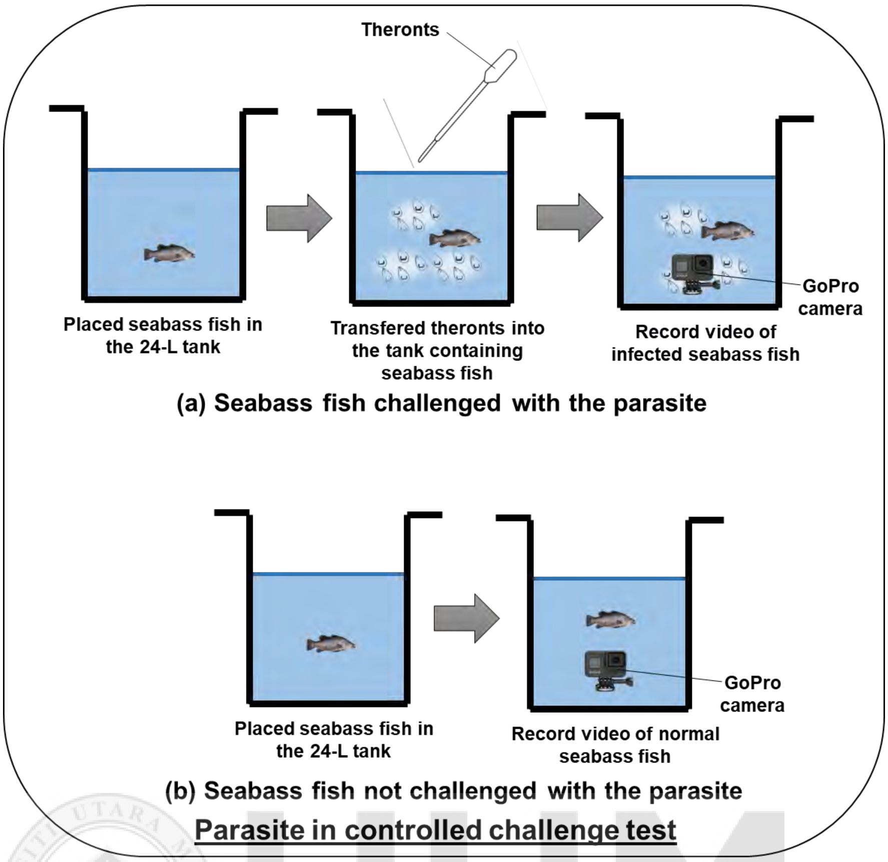


Figure 3.4: *Overview Procedure for Underwater Fish Image Acquisition*

Dataset Preparation

The video clips were recorded under natural lighting conditions using a GoPro Hero 9 camera which was set up to default settings of 4K (3840 x 2160 pixels) resolution at 60 frames per second (fps). The videos acquired from GoPro were first pre-processed (software: MATLAB R2021a) to extract four frame per seconds and all extracted still images were stored in JPG (.jpg) format with the original resolution (3840 x 2160 pixels) to create a raw dataset for further image analysis. Thereafter, the still images extracted were manually compared and screened to identify and filter out images with no presence of fish. The aspect of image representation is crucial, especially in the case of fish images taken at close range. It is essential to ensure that the fish's features were captured and represented in the images to enable accurate analysis and detection. The dataset used for this study contain images of normal fish and protozoan white spot infected fish.

3.4 Morphological Feature Identification

The images acquired from the experiment conducted at NaFisH during fish image acquisition phase were thoroughly examined to identify the essential morphological feature of protozoan white spot disease in the infected fish. This process was carried out in collaboration with domain experts who possess in-depth knowledge and expertise in fish parasite. At this stage, morphological feature was identified from the captured images, that are indicative of the early clinical signs of the disease. The feature plays a crucial role during training of the CNN because CNN will learn to effectively differentiate between normal and infected protozoan white spot. Additionally, dataset validation for the captured underwater fish images was also conducted with domain experts from NaFisH. During the data validation process, the domain experts carefully reviewed the dataset and completed a dataset validation form, as in the Appendix A. The involvement of domain experts in the data validation process ensures that the dataset used is of high quality and contains reliable information. Their expertise and knowledge in fish health added credibility to the study's findings and conclusions.

3.5 New Procedure for Protozoan White Spot Disease Detection

During this phase, the raw underwater images were subjected to computer processing, specifically focused on detecting protozoan white spot disease. The detection process of new procedure involved two main processes: image enhancement and classification. In the image enhancement process, CACC was applied to improve the quality and visibility of the underwater images, thereby enhancing the features relevant to the detection of the disease. Subsequently, the enhanced underwater images were used during the training and testing of CNN model. The CNN model trained and then tested to classify the images into two categories: protozoan white spot infected fish or normal fish. The model utilized its learned patterns and representations to predict the label classes accurately. The simplified flowchart of the new procedure is illustrated in Figure 3.5, providing a simplified process flow of the procedure in detecting protozoan white spot disease. All experiments were conducted using MATLAB R2021a and executed on a high-performance computer system running Windows 11 operating system. The computer system is equipped with 64GB of memory and an Intel Core i9-10980HK Processor of 2.40GHz up to 3.10 GHz. Additionally, the system is enhanced with an NVIDIA GeForce RTX3080 GPU to handle computationally intensive tasks efficiently.

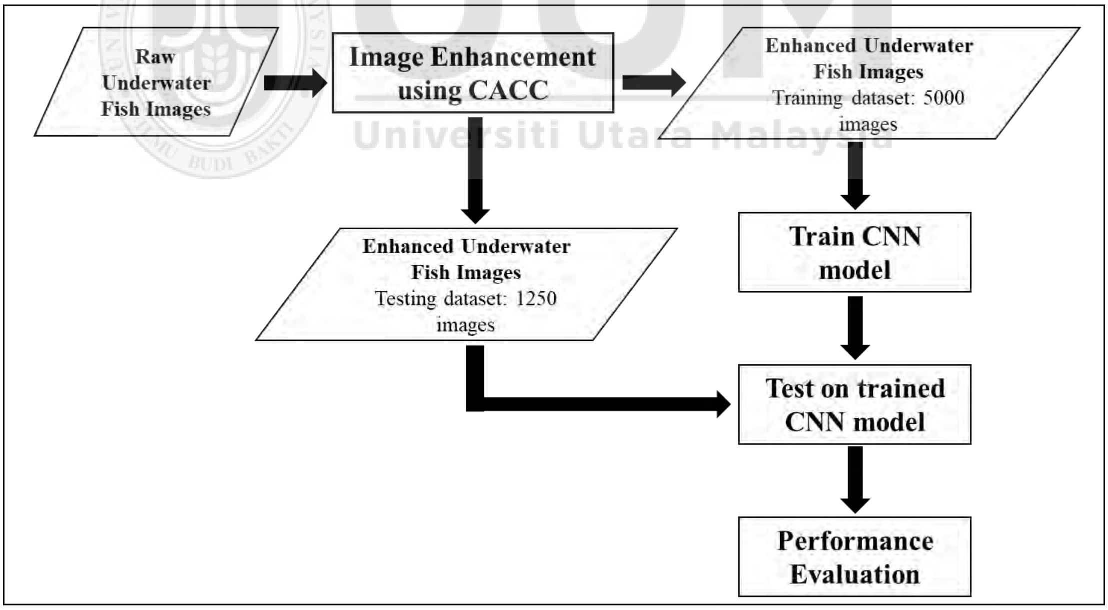


Figure 3.5: *Simplified Process Flow of the Procedure*

3.5.1 Image Enhancement

For underwater application, image enhancement is the most important step to improve underwater image quality that is susceptible to poor contrast, poor visibility, colour distortion and noise. Besides, to get the best performance result of CNN during the classification stage, it is important to provide input images with enhanced quality. CACC technique was chosen in this study as the technique for image enhancement. Thus, raw underwater images were then gone through this enhancement process using CACC, a combination of DCP, ALCC, and CLAHE (as mentioned in section 2.5.1). The simplified flowchart of CACC is shown in Figure 3.6.

CACC began by applying DCP algorithm to eliminate haze from the image. Then, CLAHE algorithm was applied to enhance the contrast of the image. The CLAHE algorithm works on small areas of the image rather than the entire image and increases the contrast of each tile to match the desired distribution parameter. Furthermore, ALCC algorithm was applied to further refine the image quality and to improve the overall visual appearance of the image, ensuring that colours are well-balanced and visually pleasing. By combining DCP, CLAHE, and ALCC algorithms, the CACC technique aims to overcome the limitations of individual algorithm and produce high-quality images with improved contrast, reduced haze, and enhanced colour coherence. The dataset underwent division into distinct training and testing datasets, facilitating the training of CNN model and subsequent evaluation of its performance. The training dataset served as the foundation for model fitting, while the testing dataset was instrumental in generating predictions. These predictions were then compared against the original labels, allowing for an assessment of the approach's effectiveness in accurately predicting outcomes. Following the methodology proposed by Gupta et al. (2022), the dataset was split into a train and test set using an 80:20 ratio. This split ensures that the CNN model is trained on a substantial number of images while still having a separate set of images to evaluate its performance.

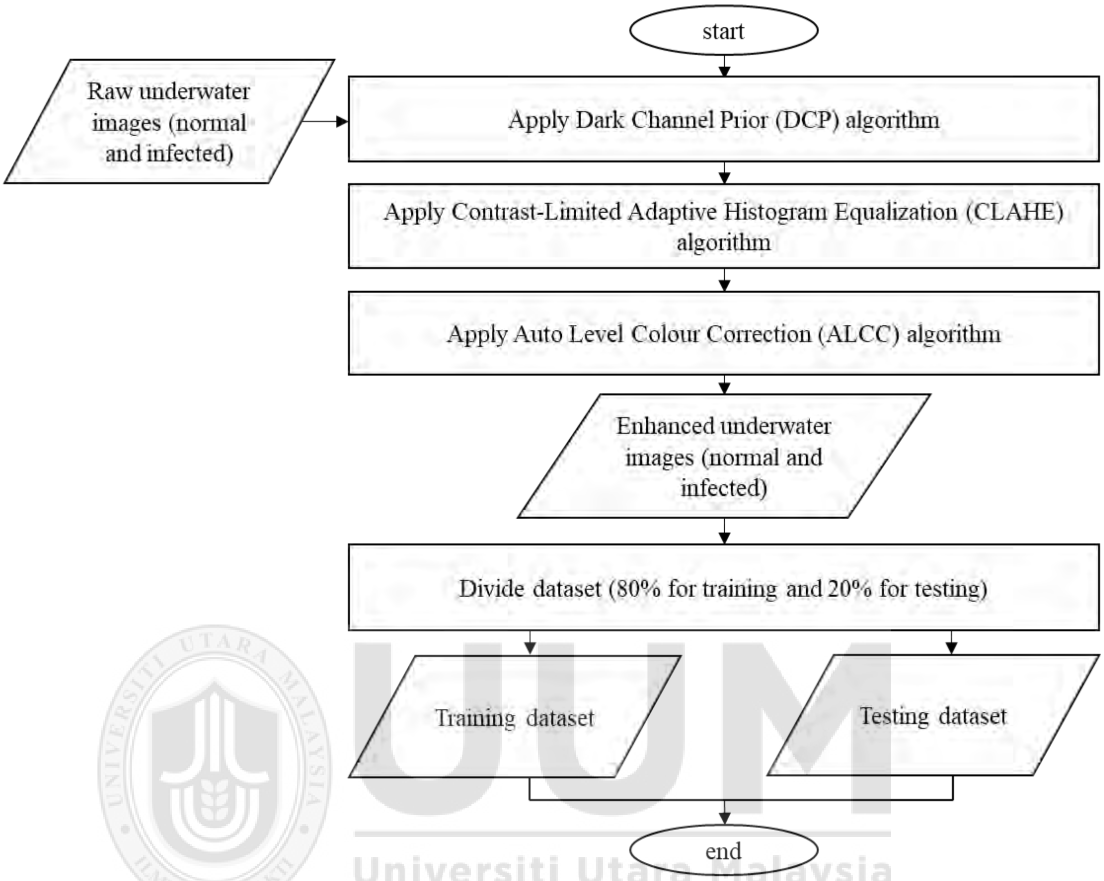


Figure 3.6: *Simplified Flowchart of CACC Technique*

3.5.2 Classification

The next process for protozoan white spot disease detection after image enhancement is the classification. The dataset for the classification has two (2) sets of classes. One is the protozoan white spot infected fish images, and the other one is normal fish images. Out of the total 6,250 images gathered, a division of 80% was dedicated to the training phase, allowing for a thorough learning process and the remaining 20% served a crucial role in the subsequent testing phase that depicts in Table 3.1. To elaborate further, the training dataset encapsulated 5,000 images, enabling the model to learn and adapt comprehensively. Meanwhile, the testing dataset was carefully curated with 1,250 images, aiming to rigorously assess the model's performance and generalizability. One significant aspect to highlight is the consistency maintained across these datasets. The fish samples used for training the model were intentionally carried over into the testing phase. This deliberate continuity ensures that the model was evaluated on familiar fish samples, enhancing the reliability and comparability of its performance across both training and testing sets.

Table 3.1: *Overall Dataset Splitting*

Fish	Training images	Testing images
Normal fish	2 000	625
Protozoan white spot infected fish	3 000	625
Total	**5 000**	**1 250**

In this study, the classification process to classify protozoan white spot disease was using the CNN algorithm with different types of pre-trained architectures including GoogleNet, ResNet101, AlexNet, ResNet50 and Vgg16Net from MATLAB's Deep Learning Toolbox. Through the inclusion of multiple CNN architectures, this study aimed to systematically assess these models, offering a standardized framework for their evaluation. This meticulous approach provided invaluable insights into the distinct capabilities of each architecture, revealing which model excelled in learning and extracting crucial features from the dataset. By subjecting these architectures to rigorous comparison within a controlled environment, the study illuminated the specific strengths and weaknesses inherent in each model's ability to comprehend and leverage the dataset's information. This methodological strategy facilitated a nuanced understanding of how various CNN architectures perform when confronted with the task of feature extraction and learning relevant patterns from the given dataset.

In order to work with specific architectures, it is necessary to resize all the images in the dataset to the respective default image size required by each architecture. For instance, AlexNet requires images with dimensions of 256×256×3 pixels. Similarly, ResNet101, GoogleNet, ResNet50, and Vgg16Net have a default image size requirement of 224×224×3 pixels. To account for variations in image sizes, the ‘augmentedImageDatastore’ function from MATLAB was utilized to uniformly resize to a desired size or aspect ratio, which can be beneficial for subsequent analysis tasks.

In the domain of DL, CNN is a model comprised of multiple network layers which each layer holds unique characteristics to process the input data and send it to the next layer. CNN starts with an input layer where the input layer took the 3-D output images from the image enhancement stage as the input images of CNN. The size of the image was initialized based on the requirements of the specific architecture. Input image, I is represented as $I = m \times n$ where m and n represent the rows and columns respectively. Thus, the image input layer, In_p by a function is represented as Equation 3.1 where p is a deep learning architecture model.

$$p = In_p(I, D) \qquad \textit{Equation 3.1}$$

In the convolutional layer, convolution operation was performed to extract features from the input image I using multiple different kernels or filters. Key features such as edges, orientation, and patterns are learned by the machine in this convolutional layer. The input image I was analysed pixel block by pixel block by each kernel, with the results being combined to form a feature map, f_m as in Equation 3.2 where k is the filter window, d is the stride, and r_l is rectified linear unit (ReLU) activation function. ReLU operation was applied to the f_m in order to increase non-linearity in the network. To put it in another way, ReLU replaces the negative values in the f_m with zero.

$$f_m = Conv\ (I, k\ , d, r_l) \qquad \textit{Equation 3.2}$$

Following that, the batch normalization layer assessed the mean and variance for each f_m. Through the batch normalization process, the application of significantly higher learning rates becomes feasible without the need to meticulously manage initialization concerns. The information then passed to the next layer in hidden layers which was the pooling layer. This pooling layer functions in down sampling the f_m generated by the previous layer, resulting in a reduced dimensionality of f_m. Its primary objective is to extract important information while omitting less relevant or redundant details, enabling the subsequent layers of the network to operate on a more informative representation. Max pooling was used by partitioning the input into pooling regions and selecting the maximum value within each region. The pooling operator progresses by selecting the maximum value among a set of T activations. Subsequently, each n-th max-pooled band comprises K-related filters as in Equation 3.3,

$$p_{k,m} = \max(\, h_{j(m-1)U+t}) \qquad \textit{Equation 3.3}$$

where the pooling shift operation $U \in \{1, 2, 3 \dots, T\}$ allows for overlapping pooling regions when $U < T$. Consequently, this process reduces the dimensionality of the K convolutional band to N pooled bands, where $N = \frac{(k-T)}{U+1}$. The final layer is represented as $p = [p_1, p_2 \dots p_N] \in\ T^{N.J}$.

Following that, the pooled f_m was flattened into a one-dimensional vector, as in sequential column (a long vector). This flattening process essentially collapses the spatial information into a sequential format, which was necessary for the fully connected layers. Towards the end of a CNN, one or more fully connected layers were commonly employed. Fully connected layers were responsible for learning and extracting high-level representations from the flattened input. Each neuron in the fully connected layer was connected to every neuron in the preceding layer. This connectivity allows the fully connected layer to capture complex relationships between features and make predictions based on the learned representations. Within the fully connected layer, neurons conduct a linear transformation on their input, followed by a subsequent nonlinear transformation as described as in Equation 3.4,

$$Y = f\left(\sum_{i=1}^{nH} W_{jk} X + B\right) \qquad \textit{Equation 3.4}$$

where *f* representing the activation function, X as the input, W signifying the weight matrix, j denoting the number of neurons in the previous layer, k specifying the neuron in the current layer, and B representing the bias weight. Maintaining an equivalent number of output nodes in the final fully connected layer is crucial, aligning with the number of classes under consideration, in this case, infected or normal classes. At this step, the error was calculated and then backpropagated. Adjustments were made to the weights and feature detectors to improve the overall performance of the CNN model. The processes were repeated until the model is a well-defined with trained weights and feature detectors, at which point the model was considered completed.

Finally, the output of the fully connected layers was fed into a Softmax to produce the final class probabilities or regression predictions. The Softmax function calculates the probabilities assigned to each class, deriving from the output produced by the final fully connected layer. This Softmax function is represented as Equation 3.5.

$$softmax(y_i) = {exp^{(y_i)}}\Big/{\sum_i \exp\,(y_i)} \qquad \textit{Equation 3.5}$$

Therefore, by combining the information gathered by the layers, the CNN be able to output the label for the image either the image contains the protozoan white spot infected fish or normal fish. The overview of the classification using CNN and simplified flowchart of classification using CNN are shown in Figure 3.7 and Figure 3.8 respectively.

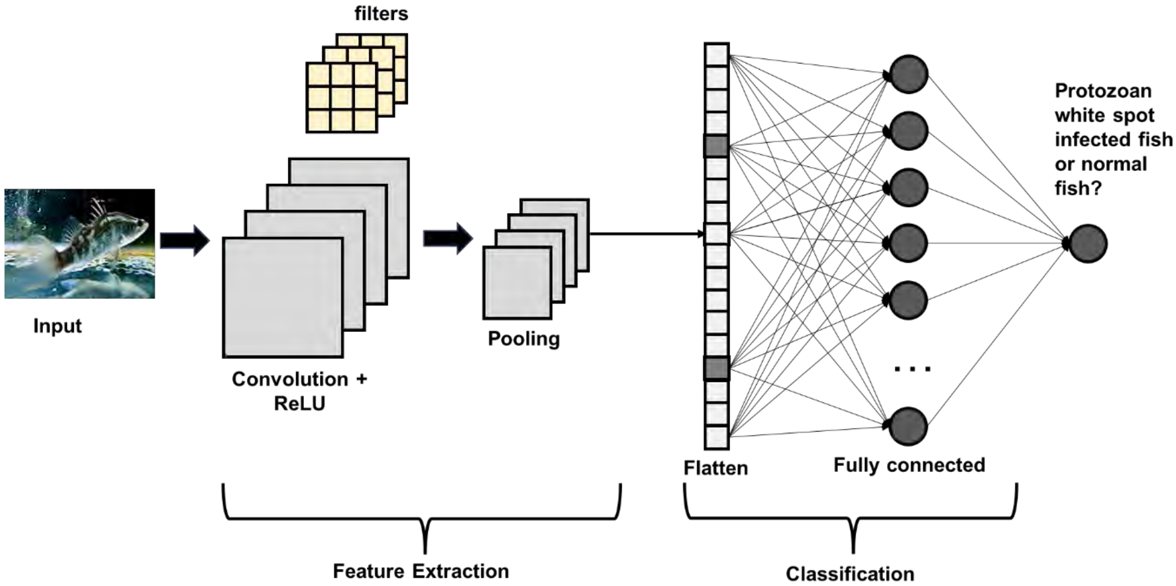


Figure 3.7: *Overview Classification using CNN*

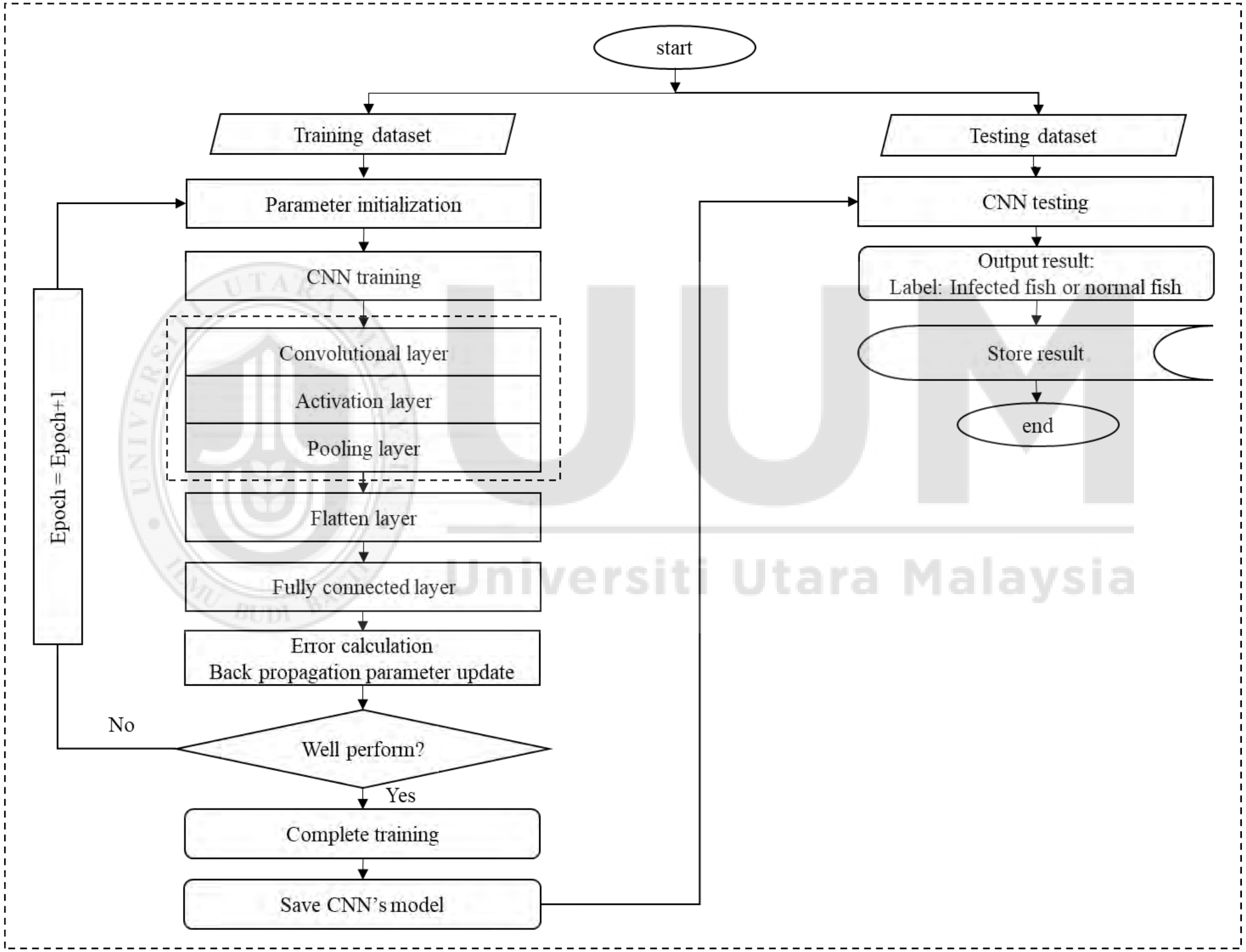


Figure 3.8: *Simplified Flowchart of Classification using CNN*

During the training process of the CNN model, several settings and parameters were defined to optimize the learning process. These settings were kept consistent across all CNN model architectures for fairness and comparison purposes as summarised in Table 3.2. The network was trained using the stochastic gradient descent momentum (sgdm) optimizer with a learning rate of 0.0003, and the maximum number of epochs was set to 6 given with the validation data and frequency. To efficiently process the training data, it was divided into mini batch of size 4 and to introduce randomness and prevent overfitting, the data was shuffled after every epoch. By setting these parameters consistently for all model architectures, the training process maintains fairness and ensures that any observed differences in performance can be attributed to the architectural variances rather than variations in the training settings.

Table 3.2: *Summary Parameters for CNN model*

Parameter	**Type/Value**
Activation function	ReLU
Pooling	Max pooling
Maximum epochs	6
Initial learn rate	3.00E-04
Size of mini batch	4
Optimizer	stochastic gradient descent momentum (sgdm)
Shuffle	every-epoch

3.6 Performance Evaluation

This section focuses on evaluating the performance of the new procedure based on the results obtained in the previous phase. The performance evaluation was conducted using various metrics. The first metric used was training accuracy, which indicates how well the trained convolutional neural network (CNN) performs during training process. It measures the accuracy of the model's training performance, providing insights into its generalization capabilities.

Additionally, the learning capability of the CNN was evaluated using a confusion matrix (CM) on testing dataset. The CM is a two-dimensional matrix that displays the target classes and the predicted classes as rows and columns, respectively. It provides insights into class-specific and overall classification accuracies. An example of a CM is shown in Figure 3.9. The confusion matrix (CM) is a pivotal tool in evaluating the performance of a classification model like the one inferred by the provided source code (refer to Appendix B) for testing image dataset. The testing dataset played a crucial role in the prediction during testing phase, leveraging the trained models to foresee outcomes. The code iterates through the testing dataset, predicting the classes using a pre-trained CNN model. For each image, the code accumulates the predicted categories either infected or normal classes. These predictions, as highlighted earlier, underwent comparison with the actual/target labels, enabling a thorough evaluation of the approach's accuracy in predicting outcomes reliably and effectively. Based on this information, the CM was constructed to establish a matrix where the rows represent the actual/target classes, and the columns depict the predicted classes.

To calculate the testing accuracy from the CM, the diagonal elements (true positives) were summed up, representing the instances where the predicted class matches the target class. Then, this sum was divided by the total number of images in the testing dataset. This division yields the overall accuracy of the CNN model's predictions across the entire dataset, computed using Equations 3.6. This approach allows for a comprehensive evaluation of the model's classification performance, considering both correct and incorrect predictions across different classes. Integrating the CM evaluation into the testing process provides a comprehensive assessment of the CNN's classification capabilities beyond a simple overall accuracy metric.

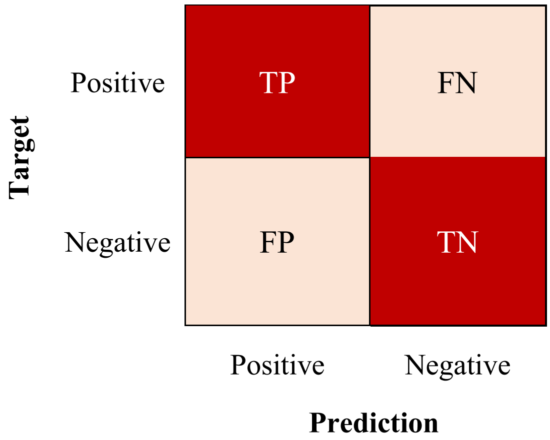


Figure 3.9: *Confusion Matrix*

$$\text{Accuracy (\%)} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100 \qquad \textit{Equation 3.6}$$

In addition to the technical aspects, the evaluation process involved gathering feedback and insights from experts and researchers in the relevant domain field. To gather this feedback, a set of survey questionnaires was prepared to the experts. These questionnaires, which are provided as examples in the Appendix C, aimed to collect valuable insights and opinions regarding the performance of the proposed new procedure. The questionnaire was divided into five sections, with the first section (section A) consisting of personal information about the respondents and section B contains several general questions related to the standard procedure for fish disease detection. The questions in section B were derived from previous studies conducted by Aftabuddin et al. (2016) and Hasan et al. (2014), incorporating elements of their methodologies and discussions pertaining to fish disease and aquaculture management. Meanwhile, sections C, D, and E were designed as Likert-scaled questions to capture information that pertain to the image enhancement capability, model performance, and overall feedback based on the System Usability Scale (SUS). By using a Likert scale, this allows experts to provide their opinions on a range of categories, and for the results to be easily analysed. The results obtained from this phase of the evaluation were analysed and discussed in the subsequent chapter of the study. The discussions involved interpreting the survey responses and highlighting any areas of improvement for the model. By involving experts and researchers in the evaluation process, these feedbacks add credibility and provides valuable perspectives that contribute to the overall evaluation of the developed procedure.

3.7 Summary

In summary, the underwater fish images were obtained from an experiment at the National Fish Health Research (NaFisH) in Batu Maung, Pulau Pinang. The images were acquired in their raw form and categorized as primary data, focusing on seabass fish. The dataset included images of normal and protozoan white spot infected fish, collected during a controlled challenge test involving the parasite *C. irritans*, ensuring diversity in the dataset for analysis and experimentation. Additionally, the dataset underwent validation by domain experts from NaFisH, who reviewed the dataset and identify key morphological features indicative of protozoan white spot disease in infected fish, focusing on early symptoms.

For the detection of protozoan white spot disease, the new procedure involved two main processes: image enhancement using CACC to improve image quality and visibility, and classification using a CNN to categorize the images as either infected or normal fish. This study utilized the CACC technique, a combination of DCP, ALCC, and CLAHE algorithms, to enhance the raw underwater images. The enhancement process began with DCP to remove haze and CLAHE algorithm was applied to enhance contrast. Additionally, the ALCC algorithm refined image quality, ensuring well-balanced colours. Pre-trained architecture like GoogleNet, ResNet101, AlexNet, ResNet50, and Vgg16Net, were employed for CNN. The output of the CNN provides classification of the images. Lastly, the procedure's performance was evaluate based on training and testing accuracy. It also involves gathering feedback from experts through a survey, aiming to understand issues in standard procedure and overall performance. The results are analysed in the subsequent chapter to identify areas of improvement and benefit from domain-specific knowledge, enhancing the procedure's overall evaluation.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Overview of the Chapter

In this section, a comprehensive analysis of the performance results obtained from various experiments conducted on the acquired underwater fish image dataset using the proposed procedure for detecting protozoan white spot disease is presented. The performance evaluation is a crucial step to assess the effectiveness of the new procedure. Detailed description of the underwater fish image dataset acquisition and morphological feature identification is explained in the initial chapter. Next, performance of the new procedure evaluated through various performance matrices in terms of technical aspect is discussed. Following that, the performance evaluated by experts also discussed. The evaluation by domain experts further strengthens the reliability of the procedure for detecting protozoan white spot disease using AI method based on the underwater fish images.

4.2 Underwater Fish Image Acquisition and Morphological Feature Identification

Data acquisition is indeed a crucial aspect of conducting research, and in this study, it played a fundamental role in preparing the dataset. The underwater fish images were captured during an experiment conducted at NaFisH Batu Maung in Pulau Pinang and the acquired images were in their raw and unprocessed form, saved in JPG (.jpg) format, with a resolution of 3840 x 2160 pixels. The dataset consisted of a total of 6,250 images, with 80% (5,000 images) allocated for training the model. Within the training dataset, 40% (2,000 images) were normal fish images, and the remaining 60% (3,000 images) were images of fish infected with protozoan white spot disease. The training dataset was further split into a train set and a validation set, with a ratio of 70% and 30%, respectively. The remaining 20% (1,250 images) of the dataset were used to test the model's performance. Example of the underwater fish image dataset is provided in Figure 4.1, with the left-side portion displaying normal fish images (a) and the right-side portion displaying images of fish infected with protozoan white spot disease (b). These sample images illustrate the dataset, providing a variety of examples for the model to learn and make accurate predictions.

The dataset captured from the experiment conducted at NaFisH during fish image acquisition phase is reviewed to identify the morphological features of the protozoan white spot infected fish that reflecting on the external clinical sign of this disease. The primary morphological feature identified as an early clinical sign of protozoan white spot infection is the presence of white spots on the fish's body as shown in Figure 4.2. These white spots were observed to have specific characteristics: appeared whitish in colour, oval to spheroid in shape, and exhibited an opaque appearance. The parasites exhibit a round to spherical morphology and vary in size, typically ranging from 0.3 to 0.5 millimetres. The identification of these morphological features is of utmost importance, as they serve as key indicators for distinguishing between normal fish and fish infected with protozoan white spot disease. Identifying this crucial morphological feature as an early external clinical sign ensures the accuracy and reliability of the new procedure, contributing to its effectiveness in early detection and detection of the disease in underwater images.

(a) Normal (b) Infected fish

Figure 4.1: *Sample Images of (a) Normal Fish and (b) Protozoan White Spot Infected Fish*

Figure 4.2: *(a) & (b) Whitish Spots on Fins of Infected Fish*

Moreover, the significance of high-quality data in research cannot be overstated (Ercole et al., 2020). It not only facilitates precise interpretation of findings but also lays a robust groundwork for future studies, thereby enhancing the credibility of research outcomes. Any inadvertent errors or inaccuracies in data could raise concerns regarding research integrity, underscoring the pivotal role of data integrity in upholding the study's reliability. A proactive measure to mitigate the risk of erroneous or unreliable data is through data validation (Breck et al., 2019). To ensure and maintain the data's reliability within this study, comprehensive data validation measures have been integrated into the analysis of the captured underwater fish image dataset. This process involved collaborative efforts with domain expert from NaFisH, renowned for the extensive proficiency in fish health and disease detection. The expert involved during this process meticulously reviewed the dataset, identifying specific morphological features indicative of protozoan white spot disease in fish. Throughout this meticulous review process, the expert completed the dataset validation form, a detailed record of which is available in Appendix D. According to Jan et al. (2023), validating data's validity holds paramount importance across all research domains, particularly in studies employing AI methodologies. Therefore, in such cases, ensuring both the model and the data inputs' validation is crucial to guarantee the accuracy and dependability of research outcomes (Roh et al., 2021).

4.3 Performance Evaluation of New Procedure

The results obtained are subject to in-depth analysis, utilizing a range of performance metrics to evaluate the proposed new procedure. To facilitate a comprehensive understanding of the procedure's performance, dedicated subsections are utilized to discuss the findings and output metrics. In each subsection, the analysis delves into the interpretation of the performance metrics, drawing comparisons between different aspects of the procedure's performance. The aim is to not only highlight the procedure's strengths but also identify any weaknesses or areas that require improvement. The insights derived from the analysis provide valuable information on the overall performance of the procedure.

4.3.1 Classification using Different CNN's Architectures

In this study, the performance of CNN model using several architectures including GoogleNet, ResNet101, AlexNet, ResNet50, and Vgg16Net, was compared. Each architecture was trained on 5000 samples and subsequently tested on 1250 samples. Figures 4.3, 4.4, 4.5, 4.6 and 4.7 depict the overall performance of each architecture

(GoogleNet, ResNet101, AlexNet, ResNet50, and Vgg16Net) during the training phase in MATLAB, respectively. From Figure 4.8, it is evident that the ResNet50 architecture outperforms the other architectures during the training phase, achieving a training accuracy of 99.73%. Following ResNet50, GoogleNet achieved a training accuracy of 99.33%, and ResNet101 achieved 98.00%. The high training accuracy of these architectures indicates that they have effectively learned relevant patterns and features from the training data and can accurately classify new instances. All four architectures except Vgg16Net achieved more than 95.00% training accuracy. Vgg16Net gives the worst result in comparison to the rest four architectures since the training accuracy achieved was only 60.00%. This shows that the Vgg16Net was not able to learn to distinguish features of the classes when trained.

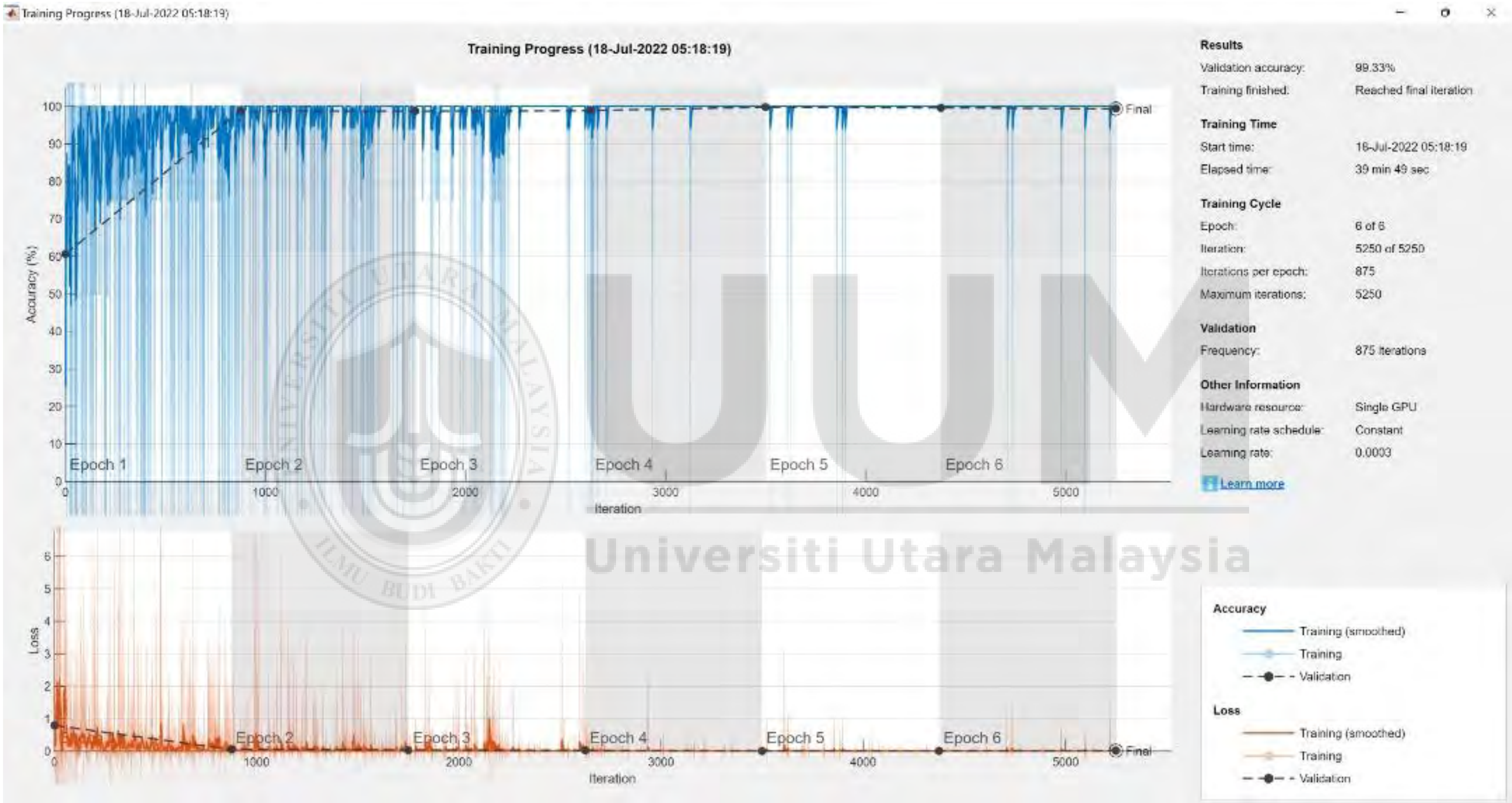


Figure 4.3: *Performance of GoogleNet Architecture During the Training Phase*

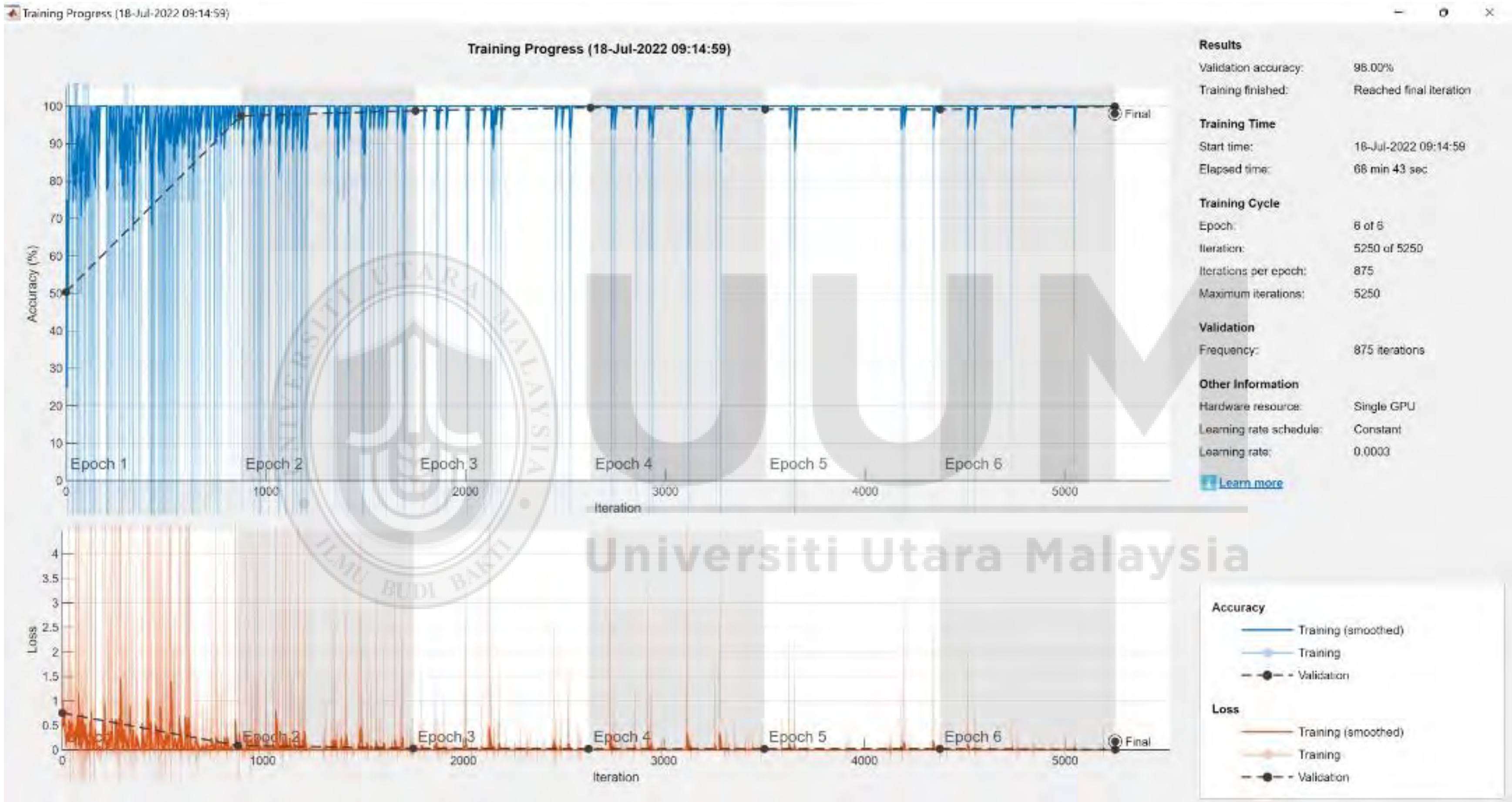


Figure 4.4: *Performance of ResNet101 Architecture During the Training Phase*

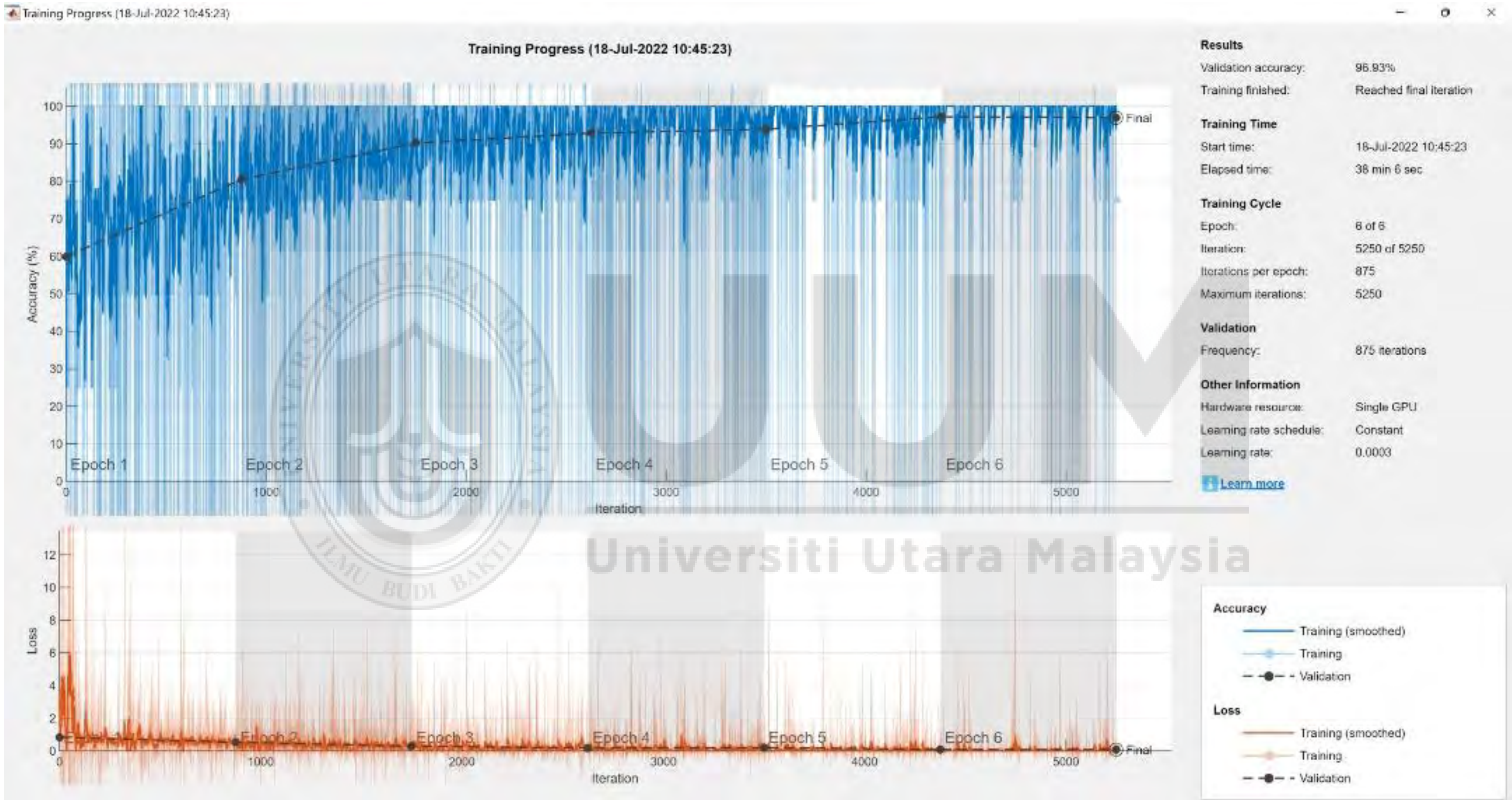


Figure 4.5: *Performance of AlexNet Architecture During the Training Phase*

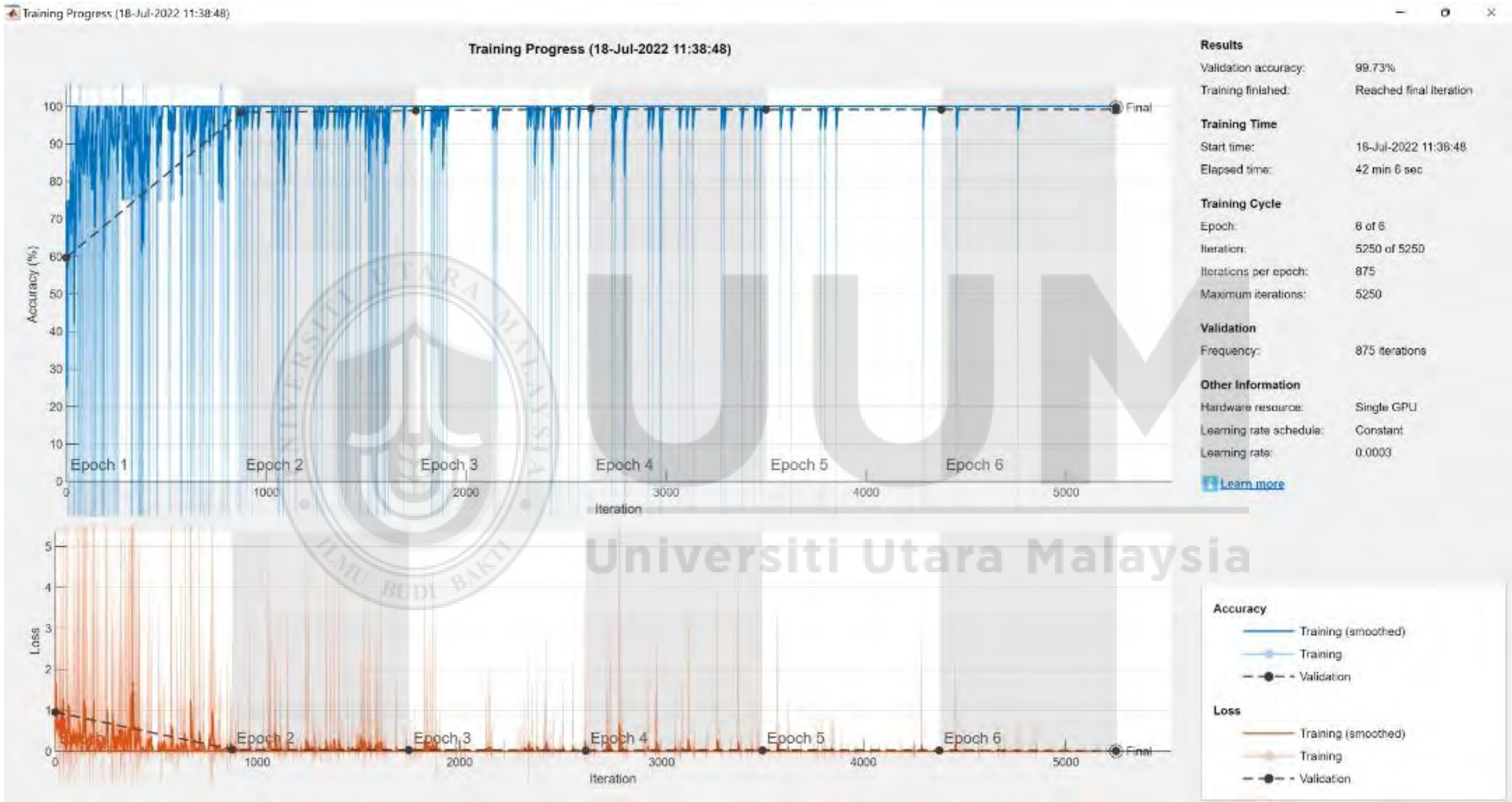


Figure 4.6: *Performance of ResNet50 Architecture During the Training Phase*

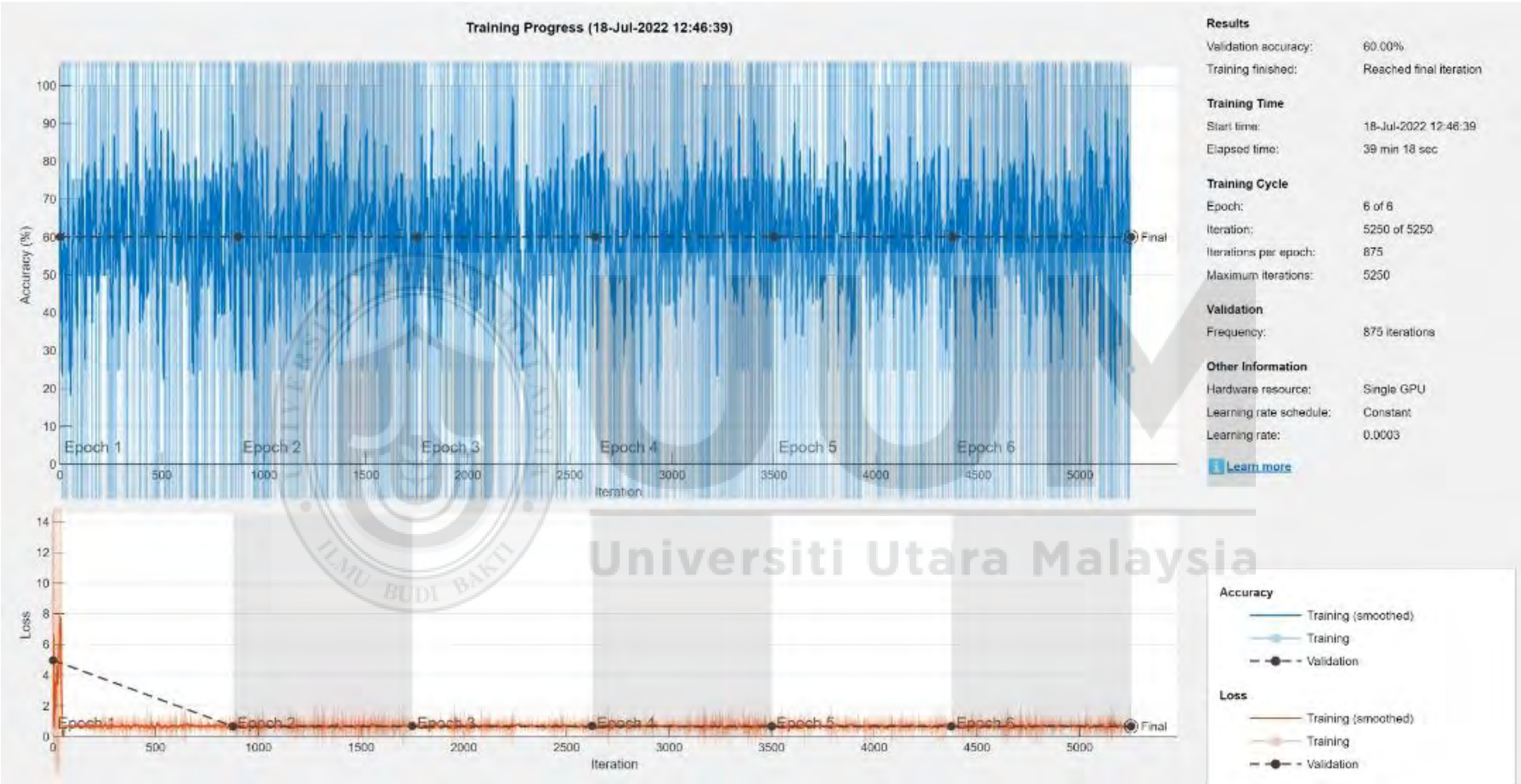


Figure 4.7: *Performance of Vgg16Net Architecture During the Training Phase*

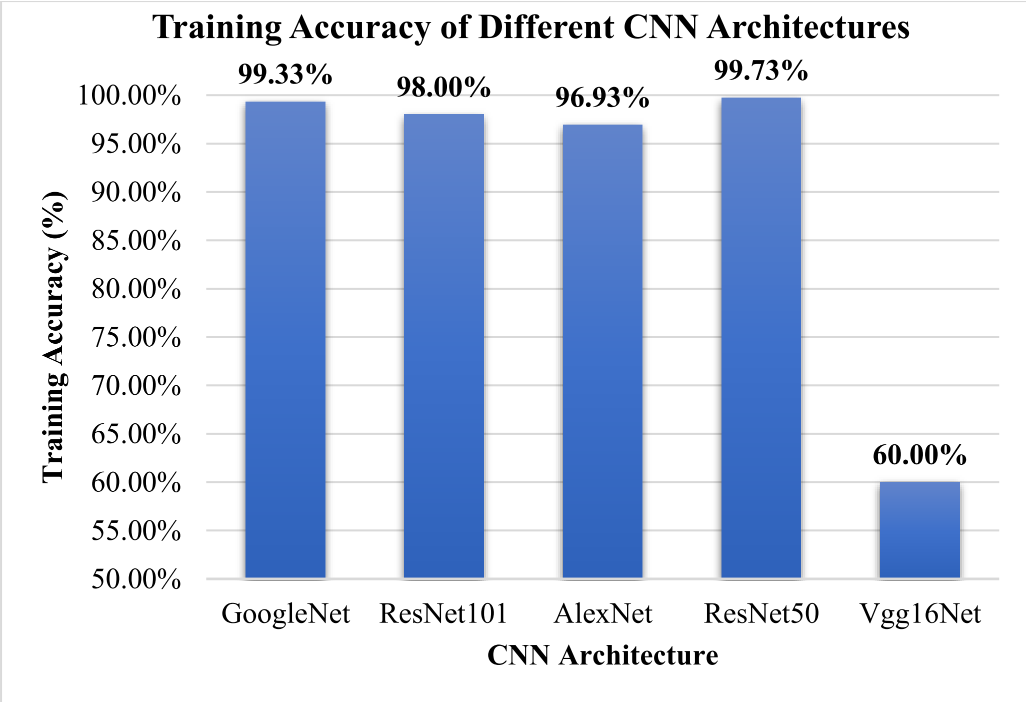


Figure 4.8: *Training Accuracy of Different CNN Architectures*

A balance between CNN training performance and CNN testing performance ensures that the proposed new procedure effectively detects protozoan white spot disease in underwater fish images. Further analysis of the CNN model's performance on the testing dataset are necessary to evaluate its generalization ability and effectiveness in detecting protozoan white spot disease in underwater images. During the training process, the model undergoes multiple iterations to improve its performance, and training accuracy was measured to assess its progress. In contrast, the testing process involves evaluating the model using an unseen dataset. As mentioned earlier, the testing dataset consists of a total of 1,250 images, with 625 images depicting normal fish and the remaining 625 images of protozoan white spot infected fish. These two classes, "normal fish" and "infected fish," serve as the target categories for classification. The CMs shown in Figures 4.9, 4.10, 4.11, 4.12 and 4.13 provide insights into how all the testing images were classified by the five CNN architectures. Based on the results obtained, the accuracy for each architecture was calculated using Equation 3.1.

Figure 4.9 presents the CM of the ResNet50 architecture, which achieved a classification accuracy of 99.52%. It correctly predicts all infected fish images, but mistakenly classifies 6 normal fish images as infected. Figure 4.10 summarizes the CM for the GoogleNet architecture, which achieved an accuracy of 98.24%, lower than ResNet50. Here, this architecture misclassifies 16 infected fish images as normal and 6 normal fish images as infected. Similarly, for the ResNet101 architecture, the achieved classification accuracy is 98.96%, as depicted in Figure 4.11. It correctly predicts 622 normal fish images but misclassifies 3 as infected. It also mistakenly predicts 10 infected fish images as normal, while correctly classifying the remaining 615 infected fish images. On the other hand, Figure 4.12 shows the CM corresponding to the AlexNet architecture, which achieved an accuracy of 95.68%. From the CM, it can be observed that 604 infected fish images and 592 normal fish images are correctly classified. This architecture demonstrates a lower accuracy compared to the other three. The CM in Figure 4.13 illustrates the performance of the Vgg16Net architecture, which achieved the lowest accuracy of 63.52% among the four architectures. It misclassifies 212 infected fish images as normal and fails to predict 244 normal fish images correctly thus bringing down the accuracy to be below than 65%.

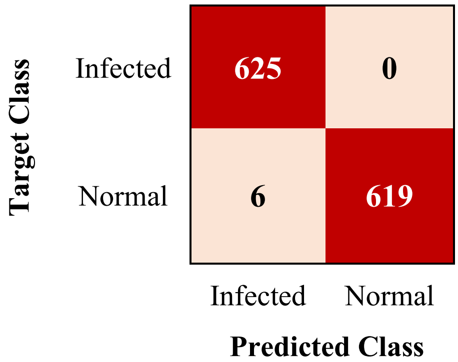


Figure 4.9: *Confusion Matrix for ResNet50*

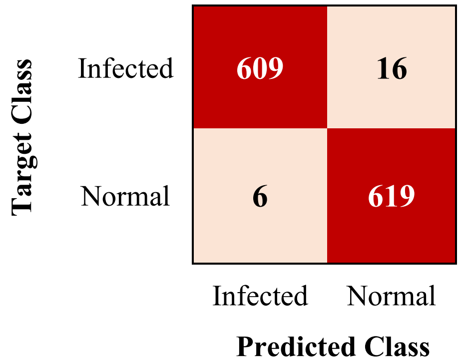


Figure 4.10: *Confusion Matrix for GoogleNet*

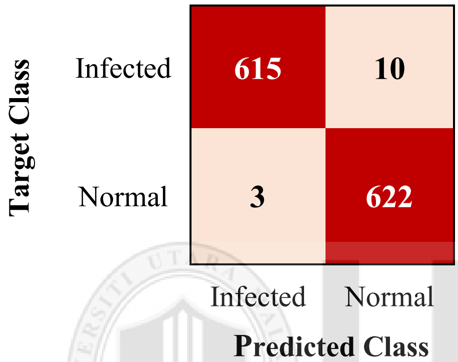


Figure 4.11: *Confusion Matrix for ResNet101*

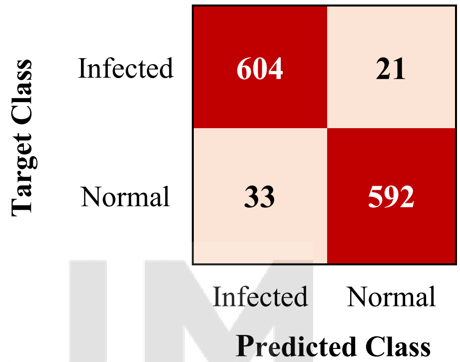


Figure 4.12: *Confusion Matrix for AlexNet*

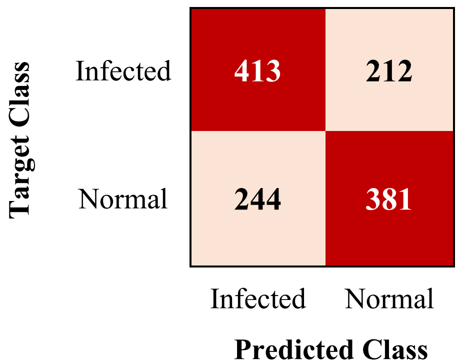


Figure 4.13: *Confusion Matrix for Vgg16Net*

Table 4.1 summarises accuracy of different CNN architectures during training and testing. Compared to the other architectures, such as GoogleNet, ResNet101, AlexNet, and Vgg16Net, ResNet50 architecture stands out with its higher accuracy, both during training and testing. This superior performance of the ResNet50 architecture is indicative of its ability to learn and capture relevant features and patterns from the training data. It showcases the effectiveness of its deep learning architecture and its capability to handle the complexities of the fish image dataset. The CM for the ResNet50 architecture, as shown in Figure 4.9, exhibits a high degree of correct classifications. It correctly predicts all infected fish images, indicating a strong ability to detect instances of disease. Additionally, only a small number of normal fish images are misclassified as infected. It demonstrates a robust understanding of the distinguishing features between normal and infected fish, resulting in accurate predictions. Overall, the findings strongly suggest that the ResNet50 architecture is the most reliable and accurate in correctly classifying between normal and infected fish images, making it a preferable choice for detecting protozoan white spot disease based on underwater images.

The findings in this study parallel those in the recent work by Deka et al. (2023) where they also showcased exceptional accuracy in classifying fish species within the Fish-Pak dataset using ResNet50. Their investigation notably achieved a maximum classification accuracy of 100% in a 20-class classification model. This striking similarity in outcomes further substantiates ResNet50's efficacy in precisely categorizing fish species within this specific dataset, highlighting its consistent and robust performance in achieving high classification accuracy. It is noteworthy that although both studies focused on different classification tasks, the alignment in results underscores the ResNet50's effectiveness. This consistent performance across diverse classification objectives bolsters the confidence in ResNet50's capability to deliver accurate and reliable outcomes across varied datasets and classification challenges.

Significantly, the values for both training and testing accuracy across all architectures (as outlined in Table 4.1) were observed to be remarkably similar. This observation implies that the CNN model exhibited proficiency not only during the training phase but also showcased consistent and reliable performance when tested on an unseen dataset. The close alignment between training and testing accuracy underscores the model's ability to generalize well beyond the training data, affirming its reliability in making accurate predictions on novel instances. As stated by Thanapol et al. (2020), minimal disparity between satisfactory training accuracy and testing accuracy typically suggests strong generalization capabilities within a model and its capability to accurately classify new and unseen images. The presentation and in-depth analysis of the confusion matrices (CMs) alongside the accuracy outcomes for each architecture offer a thorough assessment of their efficacy in distinguishing between normal and infected fish images. These findings present a comprehensive evaluation of how well these architectures perform in this classification task. The insights gleaned from these experiments are invaluable, shedding light on the practical feasibility of employing CNN as part of the proposed new procedure for protozoan white spot disease detection using underwater image. This empirical evidence contributes significantly to understanding the applicability and potential effectiveness of using CNN in detecting the diseases through underwater imaging techniques.

Table 4.1: *Accuracy of Different CNN Architectures During Training and Testing*

CNN Architecture	**Accuracy (%)**	
	Training	**Testing**
GoogleNet	99.33%	98.24%
ResNet101	98.00%	98.96%
AlexNet	96.93%	95.68%
ResNet50	99.73%	99.52%
Vgg16Net	60.00%	63.52%

4.3.2 Comparison Classification CNN Between Raw and Enhanced Images

The improvement of CNN model's performance is an area of continuous research, and the quality of the image dataset used is a crucial factor in determining the model's effectiveness. Challenges such as insufficient contrast in images due to factors like illumination or camera settings can result in a lack of distinctive features, making accurate detection challenging. Koo & Cha (2017) demonstrated the significance of image pre-processing, which greatly enhances the classification performance. A crucial aspect of image processing is image enhancement, which aims to improve the visual quality and clarity of images before feeding them into the CNN model. Hence, it is essential to explore the relationship between image enhancement technique and the performance of classification. In this section, the study focuses on understanding how image enhancement impacts the accuracy and robustness of CNN model. Additionally, the findings able to contribute to the development of guidelines and best practices for applying image enhancement technique to optimize the performance of CNN model across various domains and applications.

The study aims to investigate the influence of the CACC algorithm on CNN model and shed light on the effectiveness of enhancing image quality as a means to optimize accuracy. Following that, a comparative approach was adopted, where the raw images were compared with an enhanced images as an input for the CNN model. Among the various CNN architectures previously discussed, the ResNet50 architecture is selected for this purpose of study. The decision to choose ResNet50 is based on the outstanding performance compared to other architectures obtained in the previous section, which demonstrated its superior performance in accurately classifying between normal and infected fish images. This choice allows for a focused examination of how the combination of ResNet50 and CACC can optimize the classification accuracy and improve the overall performance of the procedure. Also, the CNN model was trained using similar parameters, ensuring a fair evaluation of the performance difference.

During the testing phase, the CNN model's performance was evaluated using both the raw and enhanced images respectively and CM was utilized to assess the model's accuracy. Figures 4.14 and 4.15 present the CM of the ResNet50 architecture with the different input images (raw and enhanced). With the raw images, the model correctly predicts all infected fish images but mistakenly classifies 21 normal fish images as infected. In contrast, with the CACC enhanced images, only 6 normal fish images were mistakenly classified as infected. The CMs demonstrate that the accuracy of the CNN model using the CACC enhanced images is 99.52%, which is higher than the accuracy achieved using the raw images (98.32%) as tabulated in Table 4.2. The improved accuracy achieved with the enhanced images can be attributed to the CACC algorithm's capacity to accentuate white spot features in the image, enhance contrast, and reduce noise, thereby leading to enhanced classification. This finding finds resonance in the research conducted by Pramunendar et al. (2019), whose study revealed the remarkable potential of CACC in enhancing classification performance. Their investigation specifically demonstrated the efficiency of CACC in fish classification task employing the back-propagation neural network (BPNN). Their results underscored how the integration of CACC significantly bolstered the classification accuracy and precision, illuminating its transformative impact on refining classification outcomes in diverse image-based tasks. This provides robust support for the assertion that CACC possesses inherent capabilities that significantly enhance the accuracy and efficiency of classification models across diverse visual recognition tasks.

By utilizing ResNet50 in conjunction with enhanced input image, it is anticipated that the classification performance was further improved, surpassing the already impressive results obtained by ResNet50 with raw input image. As a result, this combination holds great promise for enhancing the accuracy and effectiveness of the CNN model in detecting protozoan white spot disease in fish. These findings emphasize the potential benefits of employing image enhancement technique to improve the accuracy of classification since it able to highlight the importance features. Overall, the integration of CACC with the CNN shows promise in achieving higher accuracy and improved performance in detecting protozoan white spot disease in fish. These findings contribute to the understanding of how significance image quality could result in optimizing classification performance.

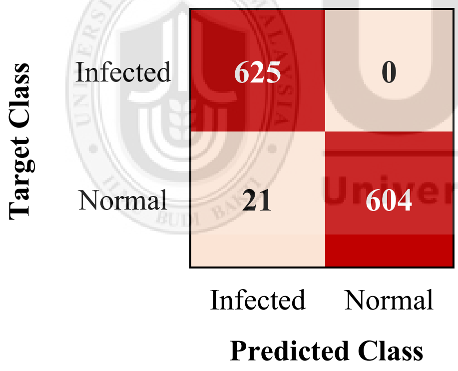


Figure 4.14: *Confusion Matrix for ResNet50 (Raw Images)*

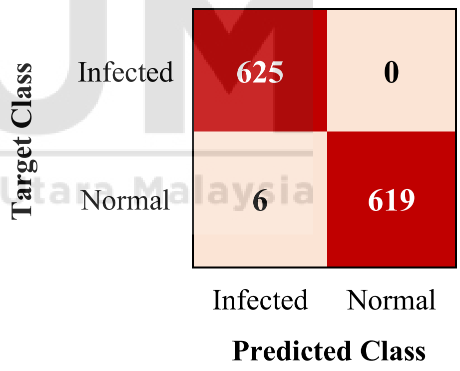


Figure 4.15: *Confusion Matrix for ResNet50 (Enhanced Images)*

Table 4.2: *Testing Accuracy of CNN (ResNet50 Architecture)*

Images	Testing Accuracy (%)
Raw	98.32%
Enhanced	99.52%

4.4 Expert Performance Evaluation

The evaluation conducted with experts in the field is aimed at obtaining impressions and feedback on the model's performance that has been developed. The experts who were involved in the evaluation are fish health researchers and academic researchers, and they were asked to provide their opinions on the model's capabilities and performance. Besides, the valuable insights of the current practises and issues in standard procedure also obtained, which contribute to a deeper understanding on the current issues and limitations. Key findings of the evaluation are discussed in this section, which provides an overview of the experts' opinions, and this is crucial to guide for future development efforts, as the feedback obtained from the experts will help identify areas that need improvements. Total of 9 experienced respondents have taken part in this expert performance evaluation phase as experts. There are 4 experts from National Fish Health Research Centre (NaFisH), 1 from Fish Research Institute (FRI) and 4 from Fakulti Perikanan dan Sains Makanan (FPSM), Universiti Malaysia Terengganu (UMT) with biography summary of the respondents are in their 30s to 50s.

4.4.1 Practises and Issues in Standard Procedure for Fish Disease Detection

More than half of the respondents rely on eye observation to early detect the fish disease in aquarium or pond. While this is common in standard procedure, it has its limitations, as detecting diseases through eye observation alone can be subjective, prone to errors, and may not detect early signs of disease. The fact that some of the respondents require assistance from fish expert in detecting fish disease highlights the complexity of the task. Relying solely on human expertise can be time-consuming, costly, and may not be readily available to everyone. In terms of the time taken, majority of respondents take 1 to 3 days to complete the fish disease detection process specifically for the case of parasitic infection. This duration is significant and can have implications for the treatment and management of the disease. Some respondents even took 4 to 6 days, indicating that the process can be even more time-consuming in certain cases. However, this could be an outlier and may not be representative of the typical detection time as the variation in detection time can be attributed to several factors, including the severity of the infection and the experience and skill level of the person conducting the observation. Delayed detection can lead to the rapid spread of diseases within the aquatic environment, potentially causing extensive damage and loss of fish populations. Therefore, implementing AI-based fish disease detection can lead to quicker detection times and minimize the loss of fish populations. The use of AI in early fish disease detection offers a promising solution to the challenges highlighted in the survey. It can significantly improve the efficiency, accuracy, and timeliness of disease detection, ultimately benefiting the sustainability of fish populations in aquariums and ponds.

All respondents agreed that conducting external gross observation on live fish is the most appropriate state for disease detection. This consensus underscores the significance of real-time observation to ensure accurate results. Apart from that, most of them agreed that the external gross observation process is sufficient to detect ectoparasite disease. This suggests that this method is widely trusted within the domain understudy. However, it’s noteworthy that one respondent believed that external gross observation may be insufficient for conclusively determining the presence of parasitic infections in fish. This dissenting opinion suggests the need for acknowledging potential limitations in the external gross observation process that should be taken into consideration when early detecting fish disease caused by parasite. Therefore, this study could be helpful in overcoming the limitations of external gross examination.

Furthermore, respondents provide varying opinions on the estimated cost for each fish disease inspection, with some suggesting a range of RM 25 to RM 50 for each inspection of parasitic infections. Others believe that the cost depends on various factors, including the number and type of samples and the specific laboratory analysis.

This underscores the complexity in estimating the cost of disease inspections. The diversity in estimated costs suggests the need for standardization or further research to determine a more accurate and consistent pricing model for inspecting parasitic infections in fish samples. In other aspect, respondents generally believe that the workload associated with disease inspection can be effectively managed by a small team of individuals, typically involving 1 or 2 persons. This may be due to the relatively small scale of their operations or the use of efficient technology and resources. Same goes to costing, all respondents unanimously agree that the cost of disease inspection should be borne by the breeder. This implies that the responsibility for covering the cost of inspection should fall on the individual or organization that owns or manages the fish breeding operation.

Other than that, respondents hold varying opinions on issues related to the external gross observation process. This diversity suggests that the challenges and concerns in external observation are multifaceted and depend on individual experiences and perspectives. Some common themes emerge from the responses, including the lack of knowledge, experience, and specialized individuals involved in external observation. This implies that there is a need for improved education and training programs for individuals engaged to enhance their expertise and competency. Environmental factors are also highlighted as having an impact on the observation process. Respondents point out that water quality, temperature, and other environmental conditions can affect both the health of the fish and the effectiveness of the observation process. This underscores the interconnectedness of fish health and environmental conditions. To conclude, the diverse opinions highlight the complexity of external gross observation in aquariums or ponds. The identified issues related to knowledge, experience, specialized individuals, and environmental factors point toward the need for education, training, and ongoing research to enhance the process. This necessitates the development of guidelines or best practices for effective early fish disease detection and prevention, ultimately ensuring the health and well-being of the fish populations in aquariums or ponds.

4.4.2 Overall Procedure Evaluation

In this subsection, the insights of experts regarding the effectiveness and performance of the procedure employed for the detection of protozoan white spot fish disease is discussed. The survey questionnaires presented in sections C, D, and E predominantly revolved around the system, which encompasses the integration of image enhancement and classification techniques. A “system” in this context is a fundamental component that outlines how the procedure operates when executing specific tasks within its operational framework. To offer further clarity, it is important to note that the term “system” was employed in the survey to denote the new procedure. This choice of terminology emphasizes the fundamental connection between the procedure and the system, both of which are used interchangeably to achieve a common objective. Section C pertains to the CACC application capability to enhance underwater images as shown in Table 4.3. Additionally, questions pertaining to the system’s overall performance and feedback are included in sections D and E of the survey, as shown in Tables 4.4 and 4.5, respectively. By gathering feedback from experts in the field, the procedure can be thoroughly evaluated, and any necessary improvements can be made in the future to ensure that it is functioning optimally.

Table 4.3: *Image Enhancement Application Capability Questions*

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Please answer the questions based on the above tasks:					
The white spot feature can be seen clearly in the second image	1	2	3	4	5
This enhancement technique gives a better image output	1	2	3	4	5
This enhancement technique is suitable to be used for underwater image	1	2	3	4	5

Table 4.4: *System Performance Questions*

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Please answer the questions based on the above tasks:					
This system is easy to use	1	2	3	4	5
The system interface is user-friendly	1	2	3	4	5
The information is well organized	1	2	3	4	5
The functions are easy to find and well-integrated	1	2	3	4	5
The speed of this system is fast	1	2	3	4	5

Table 4.5: *Overall Feedbacks Questions*

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Please answer the questions based on the above tasks:					
I felt very confident using this system	1	2	3	4	5
I would like to use this system frequently	1	2	3	4	5
I need the support of a technical person to be able to use this system	1	2	3	4	5
I think most people will easily use this system	1	2	3	4	5
Overall, I am satisfied with this system performance	1	2	3	4	5

Majority of respondents acknowledge the effectiveness of the CACC application capability of the employed procedure. This implies that the CACC's ability to enhance images, particularly underwater images, is well-received among experts. Specific mentions of improved clarity in seeing the white spot feature in the second image, highlight the practical advantages of CACC in making subtle or hard-to-detect white spot features more visible. This is a crucial aspect of early disease detection in fish. Respondents also express a positive opinion about the CACC technique providing a better image output. This suggests that CACC not only clarifies details but also improves the overall quality of the images, making them more suitable for analysis. Another important aspect is the suitability of the CACC technique for underwater images. The majority of respondents strongly agree or agree that the technique is suitable for such images. This is significant because underwater conditions often introduce challenges like poor contrast, poor visibility, colour distortion and haze, making image enhancement crucial for accurate analysis. The feedback provided by experts underscores the importance of image enhancement in the context of fish disease detection. Early detection of diseases in fish often relies on recognizing crucial features, which can be challenging without high-quality images. Therefore, image enhancement plays a pivotal role in making these external features more discernible, potentially allowing for the detection of diseases at an earlier stage when treatment is more effective.

Furthermore, the majority of respondents found the system to be easy to use. Ease of use is a critical factor when implementing AI-based for disease detection, especially in aquaculture and fisheries settings where users may vary in their technical expertise. The positive feedback regarding the user-friendliness of the system's interface is significant. A user-friendly interface ensures that users can navigate the system with ease, reducing the learning curve and increasing the likelihood of its successful implementation. In the context of early fish disease detection, a user-friendly interface can empower users to efficiently analyse and interpret data, potentially leading to quicker disease detection and response. Besides, respondents agreeing that the system's information is well-organized is essential for effective use. Access to well-organized data and information is crucial for making informed decisions regarding fish health. While most respondents found the functions of the system to be easy to find and well-integrated, the fact that one respondent chose to be neutral highlights the importance of continuous improvement. Ensuring seamless integration of functions within an AI system is crucial for maximizing its efficiency in disease detection. This feedback serves as a valuable input for further refinement of the procedure. On top of that, the majority of respondents being satisfied with the system's speed is significant. Timeliness in disease detection is critical for effective early intervention and treatment. Overall, the evaluation results suggest that the system is performing well, with most respondents agreeing on the system's ease of use, user-friendliness, organization of information, and speed.

In terms of overall feedback, majority of respondents felt confident using the system is a positive sign. Confidence in using AI-based system is crucial because it suggests that users are more likely to rely on the system for important tasks like early fish disease detection, as they trust its capabilities and accuracy. Also, the responses suggests that the system has generated curiosity and interest among the respondents in using the system frequently. Frequent use of the system in the context of fish disease detection is beneficial because it promotes regular monitoring and timely intervention, which are essential for early disease detection and control. While the majority of respondents chose "neutral" when asked if they needed technical assistance to use the system, it is essential to acknowledge that some respondents did express a need for technical help. Providing adequate technical support and training for users is crucial to ensure that the system is effectively utilized. This aspect highlights the importance of user support and education when implementing AI system. Regarding the question about whether most people would easily use the system show a mix of opinions. Some respondents agreed or strongly agreed, while others had a neutral response. This indicates that while some respondents believe the system is easily accessible, others may perceive potential challenges or barriers for a broader user base. While the majority of respondents expressed satisfaction with the system's performance, it is noteworthy to note that there are some room for improvement in certain aspects of the system to ensure that it meets the expectations and needs of all users.

Lastly, the recommendations provided by the respondents highlight several critical areas including speed, provision of useful information, dataset diversity and improved image analysis. Improving the speed of the system is an important aspect that needs to be addressed, as it can significantly affect the overall user experience. Additionally, incorporating more input in the final detection of abnormal images and improving the sharpness of the image when zoomed in can enhance the accuracy of the detection. Providing useful information such as severity factor and corresponding solutions offers actionable insights that can greatly assist fish in disease management. The recommendation to expand the system to other types of diseases from different pathogens for a more diverse dataset is a valuable suggestion, as it can potentially increase the usefulness and applicability of the system in the aquaculture industry. The suggestion to remove the background and preserve only the infected area, along with labelling the particular white spot on the fish body, can enhance the accuracy of image analysis. It is important to take into consideration all the recommendations provided by the respondents as these feedbacks are invaluable in guiding the development and refinement of the system in this domain. Incorporating these suggestions can lead to a more effective new procedure for early disease detection, ultimately benefiting the aquaculture industry by enhancing fish health management, reducing economic losses, and promoting sustainable aquaculture practices.

4.5 Summary

In summary, the dataset obtained during an experiment at NaFisH Batu Maung comprises of 6,250 images. 80% of these images (5,000) were used for model training, with 40% showing normal fish and 60% displaying fish infected with protozoan white spot disease. The remaining 20% (1,250 images) served as a test set to evaluate the CNN model's performance. To maintain data integrity, data validation was carried out on the underwater fish image dataset in collaboration with domain experts from NaFisH and morphological feature of protozoan white spot disease was also identified. Most importantly, performance of CNN model using several CNN architectures, including GoogleNet, ResNet101, AlexNet, ResNet50, and Vgg16Net was studied to determine the best architecture. It can be concluded that ResNet50 architecture outperforms other architectures with training and testing accuracy of 99.73% and 99.52%. This superior performance highlights ResNet50's ability to effectively learn and capture relevant features from the input images, proving to be the most reliable choice for protozoan white spot disease detection in underwater images.

The consistent training and testing accuracy values suggest good generalization without overfitting. Besides, CNN model's performance also assessed using both raw and CACC-enhanced images. This resulted in a higher accuracy of 99.52% when using enhanced images, compared to 98.32% accuracy with raw images. The improved accuracy with enhanced images can be attributed to the CACC algorithm's ability to emphasize white spot features, leading to better classification results. By combining ResNet50 with enhanced input images, it is anticipated that classification performance was further improved. As part of the efforts, this study had strategized the use of image enhancement technique on the degraded underwater images successfully, making the classification process more accurate in detecting the contagious protozoan white spot disease.

The survey reveals that over half of the respondents rely on eye observation to early detect fish diseases in aquariums or ponds. However, this method has limitations, including potential errors and difficulty in detecting early signs of disease. Some respondents even require assistance from fish experts, highlighting the complexity of the task and its associated time and cost constraints. Notably, most respondents take 1 to 3 days to complete the fish disease detection process, particularly for parasitic infections. While this duration is significant, it can vary due to factors like infection severity and the observer's expertise. Delayed detection can lead to disease outbreaks, making early detection crucial for effective treatment and management. Besides, there are also diverse opinions on external gross observation challenges, highlighting the need for further research. Overall, the survey underscores the complexity and importance of early fish disease detection in aquariums and ponds, highlighting the potential benefits of using AI method and the need for improved practices and research in this domain.

The survey responses affirm the effectiveness and suitability of the CACC application capability, particularly for underwater images in the context of fish disease detection. Furthermore, responses indicate the procedure designed for protozoan white spot disease detection is performing well in terms of ease of use, user-friendliness, organization of information, and speed. However, it is important to consider and incorporate several recommendations given by the experts including speed, provision of useful information, dataset diversity and improved image analysis for future research as they offer valuable guidance for the procedure's development and refinement. Addressing these aspects can help ensure the successful integration of AI method into fish disease detection practices, ultimately leading to improved fish health management and sustainable aquaculture.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Overview of the Chapter

This chapter encompasses the conclusion of this study, providing a comprehensive overview of its findings and recommendations. The following section synthesizes a detailed accomplishment of the study, drawing upon the results derived from the study conducted. Next is the contributions of the study, followed by the explanation of the limitations and recommendations for future research. Finally, the chapter concludes with a summary in the last section.

5.2 Accomplishment of the Study

The consequences of infected fish diseases extend beyond individual farmers and have broader implications for the national economy. Without taking appropriate measures to address and control contagious diseases, fish production will continue to decline, further deteriorating the overall economic situation. It is imperative to implement effective strategies and preventive measures to mitigate the negative effects of infectious diseases on fish production, ensuring a sustainable fish industry. Detection of disease at early stages is important to prevent the spreading of fish diseases and it often relies on external gross observation. The early disease detection in the standard procedure calls for continuous attention of the skilled fish experts to appropriately detect the disease using eye observation. As an alternative to the external gross observation, this study aimed to comprehensively address the objectives related to the detection of protozoan white spot disease in mariculture fish through the new procedure utilizing the AI method.

The study successfully identified and documented the morphological features of protozoan white spot disease in mariculture fish. The presence of characteristic white spots on the body of seabass fish is the indication of early external clinical signs of protozoan white spot disease as a result of the parasite infestation. Identifying these visual signs through a detailed morphological analysis is crucial for the early detection of the disease. Early detection is paramount in disease management, as it enables prompt interventions to mitigate the spread and severity of the disease. Identification of morphological features not only facilitates early detection and timely interventions but also provides the foundational knowledge necessary for the development of effective disease management strategies, ultimately benefiting both the aquaculture industry and the broader environment.

One of the significant achievements of this study was the development of the new procedure for the detection of protozoan white spot disease. This procedure introduces image-based detection which relies on the underwater images being processed by image enhancement and deep learning for enhancing and classifying images. The integration of contrast-adaptive colour correction (CACC) with convolutional neural network (CNN) for detecting protozoan white spot disease in underwater images proved to be a promising approach. The emphasis is placed on the significance of using CACC as the image enhancement technique tailored for the challenging underwater environment. In underwater imaging, various factors such as poor visibility, low contrast, colour distortion, and haze can adversely affect image quality, making it challenging to accurately detect diseases in fish. CACC addresses these issues by reducing haze, adaptively enhancing contrast and correcting colour inconsistencies in underwater images. The improved image quality obtained through CACC aids in providing better visual representations of features of protozoan white spot infected fish, which in turn improves the accuracy of disease detection. Complementing the image enhancement capabilities of CACC, CNN is a powerful DL algorithm known for its ability to learn and classify patterns directly from raw data, eliminating the need for explicit feature extraction. By training on the CACC-enhanced underwater fish images, CNN can learn to differentiate features and patterns indicative of the protozoan white spot disease better.

The study rigorously evaluated the performance of the proposed new procedure. Through extensive testing processes, it was determined that the employed procedure exhibited a high level of accuracy and reliability in detecting protozoan white spot disease. The results based on the performance metrics indicate the procedure can effectively distinguish between infected and normal fish with high accuracy, exceeding 99% accuracy. The high accuracy achieved by the new procedure is particularly crucial for contagious diseases like protozoan white spot disease as early detection and containment of the disease outbreak are of utmost importance in preventing its spread and minimizing the impact on fish populations. The ability of the proposed procedure to achieve such high accuracy in a reduced time frame enhances its potential as a valuable approach for fish disease detection in the aquaculture industry. The combination of CACC and CNN ensures that the proposed new procedure is capable of overcoming the challenges posed in the external gross observation of standard procedure. Overall, the evaluation results by domain experts demonstrate the potential of the new procedure for real application in early fish disease detection. The positive responses show a significant step towards enhancing disease control and management in the aquaculture industry.

In summary, this research has made significant strides in the field of fish disease detection, particularly in the context of detection of protozoan white spot disease in mariculture fish at an early stage. The study successfully identified the morphological features of the disease, developed a new procedure for its detection using underwater images, and thoroughly evaluated the performance of the procedure. These findings hold great promise for the aquaculture industry, as they offer a faster and more accurate means of disease detection and management, ultimately contributing to the overall health and sustainability of mariculture operations. Further research and refinement of the new procedure may lead to its practical implementation in real-world aquaculture settings, further enhancing disease surveillance and control efforts.

5.3 Contribution of the Study

Upon the successful completion of this study endeavours, it is foreseen that the outcome of this study has yields substantial benefits to both the academic community and practitioners actively engaged in the respective field. Firstly, this study's theoretical contributions are composed to enhance the current body of literature, providing empirical substantiation within the domain of disease and technology management. This is achieved through the introduction of the new procedure for the detection of protozoan white spot disease using underwater images. Practically, this innovative procedure has potentially mitigated and rectified challenges associated with human intervention-based procedure. Furthermore, it facilitates the continuous monitoring of fish health, especially by enabling the early detection of infection resulting from parasites, courtesy of AI application. Timely detection not only aids in preventing co-infections triggered by other pathogens but also acts proactively to evade unforeseen delays that could potentially escalate mortality rates in aquaculture environments.

Besides, these findings hold the promise of assisting fish experts and aquaculture practitioners in streamlining the fish detection methodologies, in line with the imperatives of Industry Revolution 4.0. Moreover, this study has the capacity to foster increased collaboration among industry stakeholders, governmental bodies, and educational institutions, all with the shared objective of imparting individuals with a technology-centric mindset. Finally, in the long term, and in alignment with the Sustainable Development Goals (SDGs), this study has the potential to support the sustainable growth of the aquaculture industry, with particular emphasis on two critical aspects which are income generation and food security.

5.4 Limitation and Future Works

Certainly, while the employed new procedure utilizing AI method marks a significant stride in the study field of protozoan white spot disease detection, there remain areas with potential for improvement and potential future work to enhance the procedure's overall performance. These key areas for future research and development can be categorized into technological approach and technical development aspects. In terms of technological approach, it is important to acknowledge that the current process of underwater fish acquisition relies on a manual procedure of recording and storing fish videos. Future efforts could focus on implementing an automated capture process that seamlessly stores recorded videos in cloud storage. Furthermore, the severity level of protozoan white spot disease plays a pivotal role in prescribing appropriate treatments and dosages for infected fish. Future research endeavours might concentrate on the development of a grading approach that assesses the morphological features of white spots and categorizes the disease into distinct severity levels. This would provide invaluable insights for fish farmers, enabling them to manage treatments more effectively.

From a technical perspective encompassing image enhancement and deep learning, one limitation lies in the fact that the current procedure can classify fish as either infected or normal but does not offer specific information about the location of white spots on the fish's body. Future work could involve the implementation of object detection techniques to precisely identify and label the areas of white spots on fish images. This would greatly enhance understanding of the disease's extent and distribution across a fish's body. Additionally, expanding the dataset to include a more diverse range of fish species and diseases would bolster the CNN model's robustness. A more comprehensive dataset would enable the new procedure to recognize and detect a broader spectrum of fish diseases accurately. By addressing these areas for improvement and embarking on further research, the proposed new procedure stands to evolve and provide even more comprehensive and precise fish disease detection capabilities. These enhancements will ultimately contribute to the growth and sustainability of the aquaculture industry by assisting fish farmers in the effective management of fish diseases and the monitoring of fish health.

5.5 Summary

The overall conclusion of this study highlights the successful development and implementation of a new procedure for detecting protozoan white spot disease in underwater images using AI methods. The integration of CACC and CNN proved to be an effective approach in improving image quality and enhancing the classification process. The proposed methodology achieved high accuracy in distinguishing between infected and normal fish, providing a valuable tool for early disease detection in aquaculture. The contribution of this study lies in several key areas. Firstly, it addresses the need for efficient and timely fish disease detection in the aquaculture industry. By automating the detection process using AI techniques, the proposed procedure offers a more immediate and reliable approach compared to external gross observation in standard procedure. This not only reduces the risk of disease outbreak and financial losses for fish farmers but also contributes to the overall sustainability of the aquaculture sector. Lastly, the contributions, limitations, and future directions presented in this study open up new opportunities for research and innovation in fish disease management and aquaculture practices.

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APPENDICES

Appendix A: Sample Dataset Validation Form

DATASET VALIDATION FORM *to identify white spot disease features

1. EXPERT

Name	
Position	
Phone	Email

2. IMAGE

 Normal	 Infected

3. CONFIRMATION (mark √ if the statement is true)

Questions	√
Protozoan white spot disease features not shown in the normal image?	
Protozoan white spot disease features could be seen in the infected image?	

I hereby confirm that all the information provided is true and correct. ☐

Signature: ______________________

Official Stamp :

Date :

Appendix B: Source Code

```
net = matfile('ResNet50.mat'); **Loads a pre-trained CNN
model stored in a .mat file named 'ResNet50.mat'.

Dataset = imageDatastore('Enhanced Testing Dataset');
**Creates an ImageDatastore object named 'Dataset' for the
'Enhanced Testing Dataset'. This is a collection of images.

TotalImage = height(Dataset.Files); **Calculates the total
number of images in the dataset.

for img = 1:TotalImage **The 'for' loop iterates through each
image in the dataset.
    filename = Dataset.Files(img); **Retrieves the filename
    of the current image.
    imagefile = extractAfter(filename,"Enhanced Testing
    Dataset\"); **Extracts the image filename after "Enhanced
    Testing Dataset".
    input = readimage(Dataset,img); **Reads the image.
    input= imresize(input,[224,224],'nearest'); **Resizes the
    image to a 224x224 size (depending on pre-trained CNN's
    architecture used).
    [pred, scores] = classify(net.net, input); **Uses the
    loaded pre-trained network to classify the resized image
    and obtains predictions and scores.
    category = string(pred); **Converts the predicted category
    to a string to show the result for label classes either
    infected or normal classes.
    scores = max(double(scores*100)); **Retrieves the maximum
    score from the prediction scores.
    accuracy = string(scores(1)); **Converts the accuracy
    score to a string to show the result for accuracy.

    inputfile = string (imagefile); **Converts the imagefile
    to a string as inputfile.
    A = {inputfile,category,scores}; **Constructs a cell array
    A containing image file name, predicted category and
    accuracy.
    header = {'Image File', 'Prediction', 'Accuracy'}; **Sets
    up header.
    xlswrite('TestingResultResNet50',header,'TableofAccuracy
    ','A1'); **Writes the header in a sheet called
    'TableofAccuracy'.
    [~,~,ev] =
    xlsread('TestingResultResNet50','TableofAccuracy'); **
    Reads the 'ev' (cell array) in the sheet containing every
    filled row and column).
    empty_row = size(ev,1) + 1; **Determines the row where the
    new data (results for the current image) should be written
    in the sheet.
    xlRange = ['A',num2str(empty_row)]; **Specify the range
    where data will be written.
    xlswrite('TestingResultResNet50',A,'TableofAccuracy',xlR
    ange); **Appends the results for each image to an Excel
```

```
    file named 'TestingResultResNet50' in a sheet called
    'TableofAccuracy'.
end **End the 'for' loop.
```

Note: This code assumes the availability of the ResNet50 model in 'ResNet50.mat', an image dataset in the 'Enhanced Testing Dataset' folder and writes the classification results to an Excel file named 'TestingResultResNet50'. Adjustments may be needed based on the specific file paths, formats, and different CNN's architecture.

Appendix C: Performance Evaluation Survey Questionnaires

Tinjauan Penilaian Prestasi
Performance Evaluation Survey

Tujuan:

Dalam kemunculan Revolusi Perindustrian 4.0 (IR4.0), percubaan membangunkan sistem pengesanan awal penyakit ikan dalam persekitaran bawah air boleh menjadi penyumbang utama kepada sektor akuakultur yang semakin berkembang di Malaysia. Sistem ini bertindak sebagai alternatif untuk mencegah penularan penyakit dengan mengesan penyakit pada peringkat awal. Sistem ini juga membolehkan pakar, penternak dan pembenih ikan mengambil tindakan segera sebelum keadaan menjadi lebih teruk.

Matlamat utama tinjauan ini adalah untuk mendapatkan maklum balas dan tanggapan pengguna terhadap sistem yang dibangunkan. Tinjauan ini turut membantu menilai kebolehgunaan sistem dan untuk penambahbaikan reka bentuk sistem.

Purpose:

In the emergence of Industrial Revolution 4.0 (IR4.0), an attempt of developing fish disease detection system in underwater environment could be the key contributor to the growing aquaculture sector in Malaysia. The system acts as an alternative to prevent the spread of the disease by detecting the disease in the early stage. The system could allow fish experts and fish breeders to undertake immediate action before the condition worsens.

The main aim of this survey is to get user impressions and feedback towards the system developed. This survey also will help to evaluate the usability of the system and to improve the design of the system.

Semua jawapan yang anda berikan dalam tinjaun ini akan dirahsiakan. Data tersebut tidak akan mengenal pasti mana-mana individu dan akan dilaporkan sebagai satu kumpulan.

All of the answers you provide in this survey will be kept confidential. The data will not identify any individual person and will be reported as a group.

Bahagian A: Maklumat Peribadi
Section A: Personal Information

1) Umur
   Age
   a. 20 – 29 tahun
      20 – 29 years old
   b. 30 – 39 tahun
      30 – 39 years old
   c. 40 – 49 tahun
      40 – 49 years old
   d. 50 – 59 tahun
      50 – 59 years old
   e. 60 – 69 tahun
      60 – 69 years old

2) Jantina
   Gender
   a. Lelaki
      Male
   b. Perempuan
      Female

3) Jenis Responden/Peranan
   Type of Respondent/Roles
   a. Penternak Ikan
      Fish Grower
   b. Pembenih Ikan
      Fish Breeder
   c. Penyelidik
      Researcher
   d. Lain-lain. Sila nyatakan. ______________________
      Others. Please state.

4) Organisasi/Kedai/Kolam
   Organization/Shop/Pond

   ____

Bahagian B: Soalan Umum
Section B: General Questions

1) Bagaimanakah anda mengesan tanda awal penyakit ikan?
How do you detect early signs of fish disease?
    a. Sendiri (Pemerhatian mata)
    Self (Eye observation)
    b. Bantuan pakar ikan
    Fish expert's help
    c. Semua di atas
    All of the above

2) Berapa lamakah masa yang diambil dari awal sehingga proses pengesahan penyakit ikan dilakukan?
How long does it take from the beginning until the process of verifying the fish disease is done?
    a. 1 - 3 hari
    1 – 3 days
    b. 4 - 6 hari
    4 – 6 days
    c. *1 – 2 minggu*
    1 – 2 weeks
    d. Lebih daripada 2 minggu
    More than 2 weeks
    e. Lain-lain. Sila nyatakan. ______________________________
    Others. Please state.

3) Bilakah keadaan yang sesuai untuk menjalankan pemerhatian kasar luaran ikan berpenyakit?
When is the suitable state to conduct the external gross observation of infected fish?
    a. Semasa ikan masih hidup
    When fish still alive
    b. Selepas ikan mati
    After fish died

4) Adakah anda bersetuju bahawa proses pemerhatian kasar luaran ikan sudah memadai untuk mengesan penyakit ektoparasit?
Do you agree that external gross fish observation process sufficient to detect ectoparasite diseases?
    a. Yes
    Yes
    b. Tidak
    No

5) Berapakah anggaran kos yang diperlukan untuk setiap pemeriksaan sampel ikan berpenyakit ektoparasit?
What is the estimated cost required for each inspection of fish samples with ectoparasite diseases?

a. RM 25 – 50
RM 25 – 50

b. RM 50 – 75
RM 50 – 75

c. RM 75 – 100
RM 75 – 100

d. Lain-lain. Sila nyatakan. ______________________________
Others. Please state.

6) Berapakah anggaran tenaga yang diperlukan untuk setiap pemeriksaan sampel ikan berpenyakit ektoparasit?
What is the estimated energy required for each inspection of fish samples with ectoparasite diseases?

a. 1 – 2
1 – 2

b. 3 – 4
3 – 4

c. 5 – 6
5 – 6

d. Lain-lain. Sila nyatakan. ______________________________
Others. Please state.

7) Adakah anda bersetuju jika kos pemeriksaan perlu ditanggung oleh penternak?
Do you agree if the cost of inspection should be borne by the breeder?

a. Ya
Yes

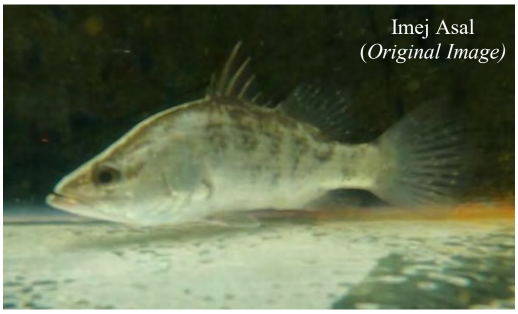
b. Tidak
No

8) Antara berikut, yang manakah merupakan isu berbangkit berkaitan proses pemerhatian kasar luaran ikan di akuarium/kolam? Anda boleh memilih lebih daripada satu pilihan.
Which of the following are the resulting issue/s related to the external gross fish observation process in the aquarium/ pond?You may choose more than one choice.

- ☐ Tiada pengetahuan dan pengalaman
- ☐ Tiada kepakaran
- ☐ Faktor persekitaran (pencahayaan, kualiti air, cuaca)

Bahagian C: Keupayaan Aplikasi Peningkatan Imej
Section C: Image Enhancement Application Capability

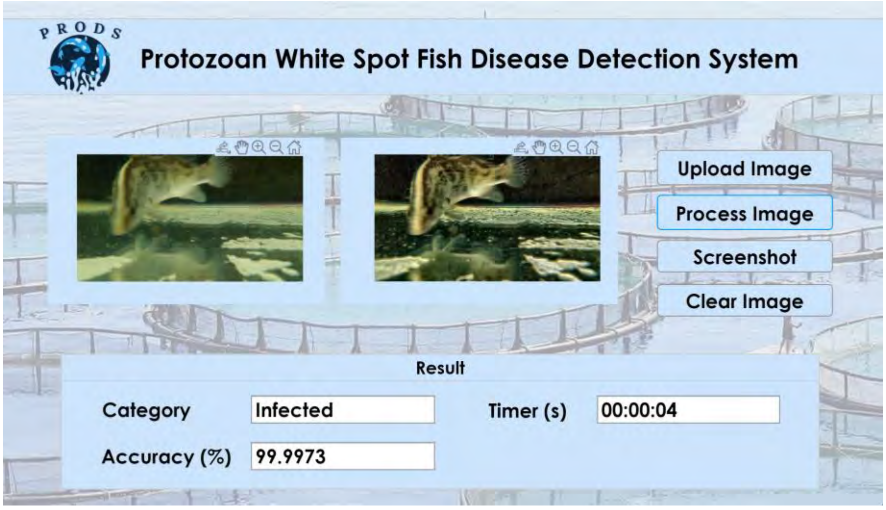
Image Enhancement Technique: Contrast-Adaptive Colour Correction



Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
1	2	3	4	5

	Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
Please answer the questions based on the above tasks: *Sila jawab soalan berdasarkan tugasan di atas:*					
The white spot feature can be seen clearly in the second image *Ciri bintik putih dapat dilihat dengan jelas dalam imej kedua*	1	2	3	4	5
This enhancement technique gives a better image output *Teknik penambahbaikan ini memberikan output imej yang lebih baik*	1	2	3	4	5
This enhancement technique is suitable to be used for underwater image *Teknik penambahbaikan ini sesuai digunakan untuk imej dibawah air*	1	2	3	4	5

Bahagian D: Prestasi Sistem
Section D: System Performance



Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
1	2	3	4	5

	Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
Please answer the questions based on the above tasks: *Sila jawab soalan berdasarkan tugasan di atas:*					
This system is easy to use *Sistem ini mudah digunakan*	1	2	3	4	5
The system interface is user-friendly *Antaramuka system adalah mesra pengguna*	1	2	3	4	5
The information is well organized *Maklumat tersusun dengan baik*	1	2	3	4	5
The functions are easy to find and well-integrated *Fungsinya mudah diurus dan disepadukan dengan baik*	1	2	3	4	5
The speed of this system is fast *Kelajuan sistem pantas*	1	2	3	4	5

Bahagian E: Maklum Balas Keseluruhan
Section E: Overall Feedback

Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
1	2	3	4	5

	Strongly Disagree *Sangat Tidak Setuju*	Disagree *Tidak Setuju*	Neutral *Neutral*	Agree *Setuju*	Strongly Agree *Sangat Setuju*
Please answer the questions based on the above tasks: *Sila jawab soalan berdasarkan tugasan di atas:*					
I felt very confident using this system *Saya berasa sangat yakin menggunakan sistem ini*	1	2	3	4	5
I would like to use this system frequently *Saya ingin menggunakan sistem ini dengan kerap*	1	2	3	4	5
I need the support of a technical person to be able to use this system *Saya memerlukan sokongan orang teknikal untuk menggunakan sistem ini*	1	2	3	4	5
I think most people will easily use this system *Saya rasa kebanyakan orang akan mudah menggunakan sistem ini*	1	2	3	4	5
Overall, I am satisfied with this system performance *Secara keseluruhan saya berpuas hati dengan prestasi sistem ini*	1	2	3	4	5

Sila kemukakan sebarang cadangan untuk penambahbaikan sistem ini?
Please provide any recommendations for improvement of the system?

END OF THE SURVEY. THANK YOU.

Appendix D: Dataset Validation Form Completed by Experts

UUM
Universiti Utara Malaysia

DATASET VALIDATION FORM *to identify white spot disease features

1. EXPERT

Name KUA BENG CHU	
Position Deputy Director	
Phone 04-6263925/926	Email kuaben01@dof.gov.my

2. IMAGE

Normal

Infected

3. CONFIRMATION (mark √ if the statement is true)

Questions	√
Protozoan white spot disease features not shown in the normal image?	√
Protozoan white spot disease features could be seen in the infected image?	√

I hereby confirm that all the information provided is true and correct. ☑

Signature

Official Stamp:

DR. KUA BENG CHU
Timbalan Pengarah Kanan Penyelidikan
Institut Penyelidikan Perikanan
Pulau Pinang

Date : 6/1/23

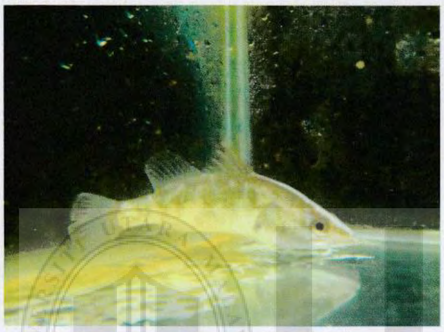
Universiti Utara Malaysia

DATASET VALIDATION FORM *to identify white spot disease features

1. EXPERT

Name	DR. PADILAH BAKAR		
Position	RESEARCH OFFICER		
Phone	011-13346628	Email	padilah@dof.gov.my

2. IMAGE



Normal

Infected

3. CONFIRMATION (mark √ if the statement is true)

Questions	√
Protozoan white spot disease features not shown in the normal image?	✓
Protozoan white spot disease features could be seen in the infected image?	✓

I hereby confirm that all the information provided is true and correct. ✓

Signature

Official Stamp: DR. PADILAH BT. BAKAR
Pegawai Penyelidik
Bahagian Penyelidikan Kesihatan Ikan Kebangsaan (NaFisH)
Jalan Batu Maung,
11960 Batu Maung, Pulau Pinang
Tel: 04-6263922 Fax: 04-6263977

Date 6.1.2023

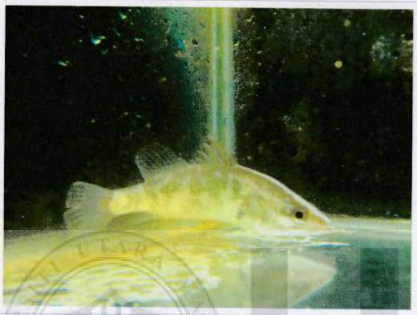
UUM
Universiti Utara Malaysia

DATASET VALIDATION FORM *to identify white spot disease features

1. EXPERT

Name ROHAIZA ASMINI BINTI YAHYA.	
Position PEGAWAI PENYELIDIK.	
Phone 012-9560321	Email rohaiza.asmini@dof.gov.my.

2. IMAGE



Normal

Infected

3. CONFIRMATION (mark √ if the statement is true)

Questions	√
Protozoan white spot disease features not shown in the normal image?	✓
Protozoan white spot disease features could be seen in the infected image?	✓

I hereby confirm that all the information provided is true and correct. ☑

Signature

Official Stamp: ROHAIZA ASMINI BT YAHYA
Pegawai Penyelidik
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Date : 06/01/2023