

**PREDICTING PRODUCTION OF CRUDE PALM OIL BASED ON
WEATHER ATTRIBUTES**

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UNIVERSITI UTARA MALAYSIA

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**PREDICTING PRODUCTION OF CRUDE PALM OIL BASED ON
WEATHER ATTRIBUTES**

**A project submitted to the Faculty of Information Technology in partial
fulfillment of the requirement for the degree
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By

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ABSTRACT

In hydrological cycle, water is the important source for rainfall forecasting. Hence, rainfall forecasting becomes a critical issue in equatorial country like Malaysia. Rainfall can affect environment and plantation activities and agriculture in Malaysia. In Malaysia, Meteorological Department collects weather information for each state in Malaysia. Rainfall prediction is important because it can produce the useful information to the palm oil production and recommending appropriate prevention climate change such as floods warning advise as well as managing water resource operations. For instances, Malaysian Palm Oil Board (MPOB) has given a lot of information about the palm oil production and its effect due to the climate changes. In this study, the analysis on weather data from the year 1996-2005 for five states such as Kedah, Kelantan, Malacca, Penang and Perak was carried out. In the initial study, regression analysis has been conducted to determine the relationship of the weather attributes and palm oil variable such as Fresh Fruit Bunches, Oil Extraction Rate and Crude Palm Oil production. However, the results were not so encouraging, therefore CBR approach has been attempted to solve the current problem then reuse the information and knowledge based that have been stored in the cases. The similarity measurement can be determined effectively between cases. Therefore, similarity measurement between cases in the rainfall and palm oil case base is the important element in CBR. The performance of each similarity measure is evaluated based on attribute's weight, and classification accuracy, In general, the similarity values achieved at most is 99.33%.

ABSTRAK

Dalam kitaran hidrologi, air merupakan sumber utama bagi taburan hujan. Oleh demikian, ramalan taburan hujan merupakan suatu isu yang penting kepada negara-negara khatulistiwa seperti Malaysia. Taburan hujan banyak mempegaruhi aktiviti sector perladanan and pertanian di Malaysia. Jabatan kaji cuaca telah menyediakan maklumat tentang taburan hujan bagi setiap negeri Malaysia. Maklumat yang didapati daripada ramalan taburan hujan boleh meningkatkan pertumbuhan kelapa sawit, memberi amaran bencana alam seperti banjir dan mengurus saluran air dengan sempurna. Disamping itu, Malaysian Palm Oil Board (MPOB) juga banyak memberi maklumat untuk meningkat pertumbuhan dan productiviti kelapa sawit, disamping itu menunjukkan memusnahkan pertumbuhan kepala sawit kesan dari bencana alam. Data taburan hujan daripada tahun 1996 hingga 2005 dianalisis berdasarkan lima negeri yang terlibat iaitu Kedah, Kelantan, Melaka, Pulau Pinang and Perak. Regression analysis perlu dilaksanakan terlebih dahulu untuk menentukan perhubungan antara parameter taburan hujan dengan parameter kepala sawit yang terdiri daripada fresh fruit bunches dan oil extraction rate. Walaubagaimanapun, hasil yang di dapati tidak memuaskan. oleh itu, pendekatan case based reasoning (CBR) digunakan. CBR merupakan satu pendekatan yang berupaya menyelesaikan masalah semasa, menggunakan maklumat dan pengetahuan sedia ada dalam kes tersebut. Dalam teknik CBR, similariti di antara kes bagi taburan hujan dan kelapa sawit boleh ditentukan melalui pengukuran similariti dan ia merupakan elemen utama dalam kajian CBR. Kebolehpayaan setiap pengukuran similariti dinilai berdasarkan pemberatan parameter dan ketepatan pengkelasan. kesimpulannya, nilai similariti yang tertinggi dalam kajian ini ialah 99.33%.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BN	Bayesian Network
CBR	Case-Based Reasoning
FFB	Fresh Fruit Bunches
NN	Neural Network
MPOB	Malaysia Palm Oil Board
OER	Oil Extraction Rate
SIM	Similarity

CHAPTER 1

INTRODUCTION

1.1 Background

Oil palm is the most productive oil seed crops in which one hectare of oil palm can produce more than 4.5 metric tons of palm oil. Malaysia and Indonesia are the two countries responsible for over 80% of the world palm oil production; the palm oil sector is one of the most important commodities in Malaysia. Malaysian palm oil has been accepted globally and recognized internationally as one of the major oils and fats in the world. The Malaysian Palm Oil Board (MPOB) is responsible for forecasting Malaysia's crude palm oil (CPO) production which is expected to reach more than 20 million tones. The Malaysian Palm Oil Association (MPOA), on the other hand, has listed out the important of palm oil industry for Malaysia and the world as follows:

1. Third pillar of nation's economy and catalyst for rural development and resultant political stability.
2. Provides direct employment to 400,000 people plus other multiplier effects and spin-offs.
3. Major foreign exchange earner RM27 billion in 2003.
4. Feeding the world Malaysian palm oil is consumed in more then 150 countries world-wide.

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