FLOOD FORECASTING USING ADVANCED MACHINE LEARNING MODEL AND FLOOD SUSCEPTIBILITY ANALYSIS AND MAPPING USING MORPHOMETRIC PARAMETERS

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DEDICATION

This thesis is dedicated to my parents, who have always prayed for my Ph.D. achievement. Special appreciation for my spouse and sons' encouragement, support, and patience during my Ph.D. journey.

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ABSTRACT

Flood catastrophes are among the natural disasters that have occurred regularly around the world. Malaysia is one of the countries that experience flood disasters on a yearly basis, most notably during the monsoon season, which runs from November to January. This study developed a novel flood forecasting model through the application of advanced machine learning (ML), deep learning (DL), and natural language processing (NLP) for sentiment analysis and text classification before a flood event, during a flood event and after a flood event. The morphometric ranking approach (MRA) was used to identify flood-susceptibility areas. Various data sources were collected including natural dimension such as rainfall intensity (mm), streamflow (cm/s), and water level (m) from Department of Irrigation and Drainage, and social dimension like text data extracted from Twitter platform. A digital elevation model (DEM) was used to process parameters for MRA with the application of geographic information system (GIS) for identifying flood-prone areas. General ML pipelines were used before building the model such as data pre-processing, data exploration to detect outliers, and filling missing values. The flood forecasting model used advanced machine learning and deep learning specifically long-short term memory (LSTM) which is suitable for time series data of rainfall and streamflow forecasting. Additionally, the model was developed using these three models: LSTM, ARIMA, and FB Prophet. The forecasting results indicated that the LSTM model has a root mean square error (RMSE) of 10.76, which is more accurate in comparison to the other models ARIMA and FB Prophet, which have RMSE values of 14.15, and 14.23, respectively. The accuracy of the model of text classification algorithm for predicting flood events is 0.87. Flood susceptibility mapping using MRA revealed that sub-catchments 5, 24, and 25 were highly susceptible to flooding. These sub-catchments were located in Jeli, Kuala Krai sub-district, and Gua Musang sub-district, respectively. In sum, this flood forecasting model is vital to provide flood information for early warning system to enable flood managers or decision-makers to make more informed plans during the flood preparation and mitigation phases, thereby minimizing the impact of floods on people, property, and the environment.

ABSTRAK

Bencana banjir adalah antara bencana alam yang kerap berlaku di seluruh dunia. Malaysia merupakan antara negara yang mengalami bencana banjir setiap tahun, terutamanya pada musim tengkujuh, yang berlangsung dari November hingga Januari. Kajian ini membangunkan model ramalan banjir baru melalui penggunaan pembelajaran mesin lanjutan (ML), pembelajaran mendalam (DL), dan pemprosesan bahasa semula jadi (NLP) untuk analisis sentimen dan klasifikasi teks sebelum kejadian banjir, semasa kejadian banjir dan selepas kejadian banjir. Pendekatan penarafan morfometrik (MRA) digunakan untuk mengenal pasti kawasan yang mudah terdedah kepada banjir.. Pelbagai sumber data dikumpul termasuk dimensi semula jadi seperti keamatan hujan (mm), aliran sungai (cm/s), dan paras air (m) daripada Jabatan Pengairan dan Saliran (JPS) dan dimensi sosial seperti data teks yang diekstrak daripada platform Twitter. Model ketinggian digital (DEM) telah digunakan untuk memproses parameter untuk MRA dengan aplikasi sistem maklumat geografi (GIS) bagi mengenal pasti kawasan yang terdedah kepada banjir. Saluran paip ML umum telah digunakan sebelum membina model seperti pra-pemprosesan data, penerokaan data untuk mengesan *outlier* dan mengisi nilai yang hilang. Model ramalan banjir menggunakan pembelajaran mesin lanjutan dan pembelajaran mendalam khususnya ingatan jangka pendek (LSTM) yang sesuai untuk data siri masa hujan dan aliran sungai. Selain itu, model ini dibangunkan menggunakan tiga model ini: LSTM, ARIMA, dan FB Prophet. Keputusan ramalan menunjukkan bahawa model LSTM mempunyai ralat min kuasa dua punca (RMSE) sebanyak 10.76, yang lebih tepat berbanding model lain seperti ARIMA, dan FB Prophet, yang mempunyai nilai RMSE masing-masing 14.15, dan 14.23. Ketepatan model algoritma pengelasan teks untuk meramal kejadian banjir ialah 0.87. Pemetaan kerentanan banjir menggunakan MRA mendedahkan bahawa sub-tadahan 5, 24, dan 25 sangat terdedah kepada banjir. Tadahan kecil ini terletak di Mukim Jeli, Mukim Kuala Krai, dan Mukim Gua Musang. Kesimpulannya, model ramalan banjir ini adalah penting untuk menyediakan maklumat banjir untuk sistem amaran awal bagi membolehkan pengurus banjir atau pembuat keputusan membuat perancangan yang lebih termaklum semasa fasa penyediaan dan tebatan banjir, sekali gus meminimumkan kesan banjir terhadap orang ramai, harta benda dan persekitaran.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

1D	-	One-dimensional
2D	-	Two-dimensional
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
ARMOR	-	ASEAN Risk Monitor and Disaster Management Review
ARIMA	-	Autoregressive Integrated Moving Average
ASEAN	-	Association of Southeast Asian Nations
BPNN	-	Back Propagation Neural Network
CNN	-	Convolutional Neural Networks
CRED	-	Centre for Research on the Epidemiology of Disasters
CS	-	Cuckoo Search
DDM	-	Data Driven Model
DEM	-	Digital Elevation Model
DID	-	Department of Irrigation and Drainage
DL	-	Deep Learning
FEWS	-	Flood Early Warning System
FFMLP	-	Feed Forward Multi-Layer Perceptron
FFNN	-	Feed Forward Neural Network
GIS	-	Geographic Information System
GRA	-	Gray Relation Analysis
HEC-HMS	-	Hydrologic Engineering Center-Hydrologic Modeling System
ICM	-	Integrated Catchment Modelling
JMM	-	Malaysian Meteorological Department (Jabatan Meteorologi Malaysia)
KNN	-	K-Nearest Neighbour
KPCA	-	Kernel principal component analysis
LSTM	-	Long- and Short-Term Memory
MED	-	Metrological Department of Malaysia

MIKE	-	Software products used to analyse, model and simulate in water environment
ML	-	Machine Learning
MRA	-	Morphometric Ranking Approach
NB	-	Naïve Bayes
NADMA	-	National Disaster Management Agency (Agensi Pengurusan Bencana Negara)
NaFFWS	-	National Flood Forecasting and Warning System
NLP	-	Natural Language Processing
PCA	-	Principal Component Analysis
RF	-	Random Forest
RNN	-	Recurrent Neural Network
SLR	-	Systematic Literature Review
SRM	-	Structural Risk Minimization
SVM	-	Support Vector Machine
WEKA	-	Waikato Environment for Knowledge Analysis, Data mining software

LIST OF SYMBOLS

AC	-	Area of circle
Au	-	Drainage basin area
Bs	-	Shape factor
Dd	-	Drainage density
Dt	-	Drainage texture ratio
Fs	-	Drainage frequency
L	-	Length of basin
L2	-	Drainage length
Lu	-	Total stream length
n	-	Number of observations
Nu	-	Total stream number
P	-	Perimeter in km
qi	-	ith observed value
Rlw	-	Length-width ratio
R^2	-	Determination coefficient
Rb	-	Bifurcation ratio
Rc	-	Circulatory ratio
Re	-	Elongation ratio
RL	-	Stream length ratio
T	-	Texture ratio
U	-	Stream order number
US$	-	US Dollars
W	-	Width of basin
X	-	A parameter value
Xmax	-	Maximum parameter value
Xmin	-	Minimum parameter value
yi	-	ith predicted value

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Problem Background

Natural disasters have a severe impact on humans' lives, properties, and the environment, resulting in the loss of the economy. Centre for Research on the Epidemiology of Disasters (CRED, 2017) revealed in its latest report published in September 2017 that 149 disasters have occurred in 73 countries in the first half of the year 2017. The impact of which resulted in 3,162 deaths, more than 80 million people affected, and more than US$ 32.4 billion in property damages. According to the report, the major disasters that occurred in Asia, South America, and Africa were floods and landslides. 44% of the events were flooded, accountable for 52% of deaths and 44% of economic damages - which make it the most expensive type of disaster. In addition, 11% of the events were landslides and caused 25% of the total death. Therefore, flood is among the natural disasters that have been repeatedly occurring in almost every part of the world

According to The ASEAN Risk Monitor and Disaster Management Review (ARMOR), the ASEAN country experienced a total of 1,604 disasters of varying magnitude between July 2012 and January 2019. Figure 1.1 shows that 85.17% of hydrological and meteorological disasters occur as a result of flooding, strong winds, tropical storms, and droughts. On the other hand, 14.83% are geophysical disasters, with the most severe landslides occurring in conjunction with earthquakes, volcanic eruptions, and relatively minor tsunami events. Additionally, the percentage of population exposed to flooding (by country) is highest in Malaysia, Vietnam, Cambodia, Lao People's Democratic Republic (Laos), Thailand, and Brunei Darussalam as indicated in Figure 1.2.

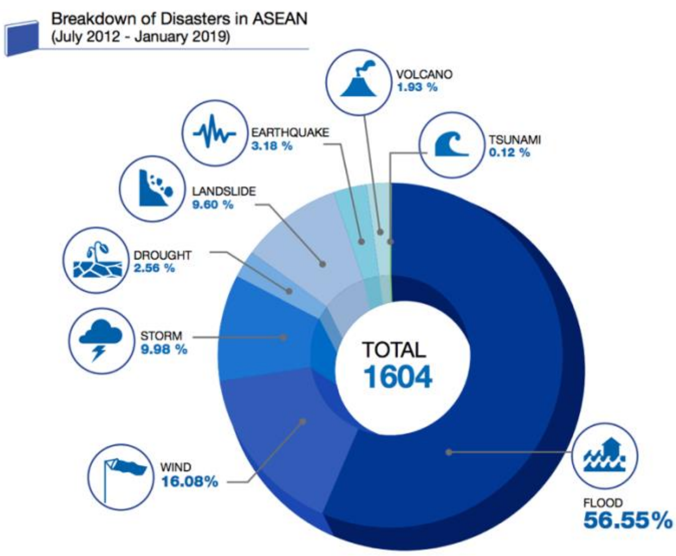

Figure 1.1 Types of disasters occur in ASEAN (Pang and Dimailig, 2019)

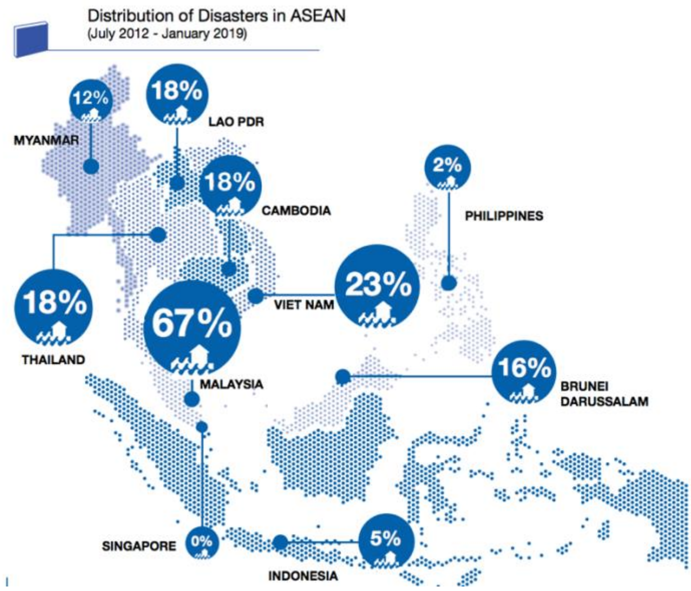

Figure 1.2 Percentage of Population Exposed to Floods (by country) (Pang and Dimailig, 2019)

Malaysia is among the countries in Southeast Asia suffering from flood disasters almost every year. Monsoon floods and flash floods are the two types of flooding that occur in Malaysia. Monsoon flooding is a result of the Northeast. The monsoon season lasts from early November to early March and brings torrential rains, particularly to Peninsular Malaysia's east coast states and western Sarawak. Flash floods are typically associated with areas of rapid development, as they are characterized by a rapid rise in water level, high velocity, and a large amount of debris. Flooding in December 2014 can be classified as the worst flood in Peninsular Malaysia's history, affecting several states, the worst of which is Kelantan(Bari *et al.*, 2021; Buslima *et al.*, 2018; Ismail and Haghroosta, 2018). The change in rainfall pattern and its uncertainty is the reason for flooding that brings heavy rainfall intensity(Ahmed *et al.*, 2018; Bopi *et al.*, 2016; Buslima *et al.*, 2018; Schanze *et al.*, 2008; Taib *et al.*, 2016) which result in prediction complexity(Bari *et al.*, 2021). On top of that, the population increase along the river valleys and rapid changes in land use often seem to make it more difficult to escape flood effects(Bari *et al.*, 2021). Therefore, to avoid catastrophic flood events, it is critical to take prevention and precaution measures included in the field of flood disaster management.

A common and systematic approach to flood disaster management covers four stages, Buslima *et al.* (2018) and Yusoff *et al.* (2018) identified the four stages which are (i) prevention or mitigation, (ii) preparedness, (iii) response and (iv) recovery. Prevention and preparation are the two stages that require actions to be taken before a flood disaster occurs, the third stage is response, the action taken during disaster and the last phase is disaster relief, rehabilitation and reconstruction activities carried out after disaster occurs. According to Baharuddin *et al.* (2015); Yusoff *et al.* (2018) the two stages of flood management such as prevention or mitigation and preparedness are the most important phases, and more attention should be given. Flood prevention and mitigation refer to activities that include structural and non-structural measures to protect areas that have been defined as flood area (Buslima *et al.*, 2018). The primary purpose of flood prevention is to reduce the human and other impacts of floods(Khalid and Shafiai, 2015; Yusoff *et al.*, 2018). A structural flood prevention plan refers to the processes for the implementation of infrastructure to mitigate flood disasters and to protect human settlements such as dam, levees, and embankments. While the non-structural measure refers to pre-disaster planning which involves controlling human activities and communities with a view to reducing property damage(Schanze *et al.*, 2008).

Flood forecasting is another non-structural measure that aims to estimate and predict the flood magnitude such as future level and flows, timing, and duration of flooding. These outputs can help provide earlier warnings of the likelihood of flooding than is possible from observations alone, and with interpreting complex situations. Flood forecasting is one of the most demanding and difficult hydrology problems, Nevertheless, it is also one of the most important hydrological problems because of its vital contribution to the reduction of economic and life losses (Jain *et al.*, 2018).

Developing flood prediction for early forecasting could reduce the impact of future floods by enabling decision makers to plan and make proper decision before flood. Department of Irrigation and Drainage (DID) Malaysia received warning advisory from Metrological Department of Malaysia (MED) on weather forecasting that measures rainfall intensity for potential location. The data is used together with hydrological data in order to analyse flood forecasting. However, the model developed by DID is based on physical theory-based model that include models based on the principles of physical processes such as rainfall-runoff model(Fernández-Pato *et al.*, 2016; Piman and Babel, 2012), hydrodynamic model (Teng *et al.*, 2017), these model are naturally complex and required knowledge from hydrologist expertise. Recently, DID is developing National Flood Forecasting and Warning System (NaFFWS), the project timeline has started from year 2015 to 2022. The system is targeted to improve forecasting from 1 day to 7 days ahead and improve waring dissemination from 6 hours to 2 days before flood.

For the process of flood forecasting model, DID is using commercial software so called InfoWork ICM for 2D approach and DHI MIKE 11 for 1D and MIKE 21 for 2D. DID adopted Sugawara's tank model for Kelantan River, Pahang River and Terengganu River to simulate the flood in InfoWork software. However, the current flood prediction approach used by DID is physical theory based model that is categorized into lumped models and distributed physically based models (Solomatine and Ostfeld, 2008) which is more complex and require human expertise and computation capability (Devia *et al.*, 2015).

Due to these major issues of traditional physical theory-based model that has been developed and fixed parameters based on the govern equation(s), data driven model (DDM) is more flexible for applying various parameters and data types. Hence, it is used to explore the related and available features for flood prediction that rely upon the methods of computational intelligence and Machine Learning (ML) approach to improve the accuracy and reliable flood prediction model that design to find the influential natural parameters such as rainfall, streamflow and social parameters such as text data at the study area which highly correlated to flooding and perform flood prediction analysis. Such a new developed model will enable decision makers or water manager to evaluate future flood situations and make early decisions for their countermeasures against the possible disaster.

1.2 Problem Statement

Flood disaster is the most significant disaster affecting every part of the world including Malaysia. In Malaysia, flood is also the most frequent disaster that has been severely damaging the society (Chan, 2015; Weng Chan, 1995). Every year, the relevant government agencies and organizations hold a meeting before the monsoon season in order to discuss the action plan to be enforced against the coming flood. Getting flood prediction information beforehand can help water manager and decision maker to plan in advance and be ready to take proper action. Hence, it is essential to have flood forecasting and prediction information in advance. In such situation with inevitable uncertainties, early flood prediction is needed to provide accuracy information on flood.

Hydrological modelling mainly used for predicting behaviour and helps to understand hydrological process. Two types of on-going research on hydrological modelling such as physical theory based model that is required large number of parameters describing the physical characteristics of the catchment (Devia *et al.,* 2015; Dibike *et al.,* 2001) such as soil moisture content, initial water depth, topography, topology, dimensions of river network etc. On the other hand, empirical model or data driven based model are considered as observation-oriented model which take only the information from the existing data without considering the features and processes of the hydrological system. Mathematical equations is involved and simultaneously derived input and output time series and not from the physical processes of the catchment. Hence, many ML techniques are applicable in this method.

InfoWork ICM and MIKE models are examples of the physically-based model currently used by DID. These models require extensive physical parameters and describe diverse hydrological cycle processes such as precipitation, evapotranspiration, interception, river flow, saturated groundwater flow, unsaturated groundwater flow, etc. These complex processes help in the application of flood forecasting and water management. However, the physical process of the hydrological cycle is complex and requires extensive physical parameters as model input, but some parameters are limited and would not be available all the time; hence, it is difficult to set up the model. Besides, to understand the complex process of the hydrological model, the requirement of proper knowledge of the water cycle, such as the rainfall-runoff process, consists of depth understanding of each process (as mentioned in the earlier paragraph) and hydraulic characteristics. This knowledge is necessary; otherwise, it will adversely affect the prediction model.

The research on the advancement of flood prediction has started for the past two decades which aims to reduce the effect of flooding such as reduction of the loss of human life, and property and environmental damage associated with flood. To imitate the complexity of mathematical expressions of physical processes of floods, ML methods contributed highly to the advancement of prediction systems providing better performance and cost-effective solutions (Abrahart *et al.*, 2004; Dawson and Wilby, 2001; Sušanj *et al.*, 2016).

Due to ML's vast benefits and potential, its popularity dramatically increased among hydrologists. By introducing novel ML methods and hybridizing existing ones, researcher aims to discover more accurate and efficient prediction models while exploring and applying different types of data. In this regard, there is a need to develop a flood forecasting model to support flood decision-makers in making proper plans and activities to reduce the impact of floods. On top of that, implementing the ML approach to process and build the models of using different data types would provide better performance with intelligent computational ability and a cost-effective process.

1.3 Research Aim and Objectives

The aim of this research is to introduce a novel flood forecasting model and flood mapping by using advanced ML approach and analyse flood susceptibly and mapping. This study provides early flood information to support decision makers to make proper plans and activities before flood occurs so that the impact of flood can be reduced.

In order to achieve the aim, the following research objectives are defined.

1. To investigate flood prediction approaches and parameters using Systematic Literature Review (SLR) approach.
2. To analyse and develop flood prediction model for flood forecasting.
3. To validate the models' performance using RMSE and MAE for flood forecasting using time series data, confusion matrix to evaluate text classification model, and DID historical record used to validate MRA for flood susceptibility mapping.

The research questions of this research focus on the accuracy and reliability of future flood information. Therefore, the following research questions must be identified.

1. Which flood prediction approach and parameters are necessary for predicting flood model?
2. How to design and develop flood forecasting model, and what are the techniques that can be implemented?

3. To what extend the proposed model and the output result can be used for supporting flood decision maker?

1.4 Scope of the Study

This research is designed to develop a novel flood forecasting model using different techniques in the field of AI that is ML for flood forecasting that apply time series data, Natural Language Processing (NLP) for sentiment analysis and text classification to classify flood event based on Twitter text data. Flood susceptibility and mapping based on morphometric approach is implemented to identify the flood prone area.

1. Data gathering and preparation are the primary part that were carefully investigated.

2. Data pre-processing of hydrological data such as rainfall streamflow and text data were done by using python and opensource library. Flood susceptibility analysis and mapping was done by using ArcMap 10.4.1.

3. This study focuses on advantage of utilizing different types of dataset by advanced ML model. Study scope does not include hydrological process models such as rainfall-runoff process.

4. The study area in this research is the Kelantan watershed. Observation data such as rainfall, water level, and streamflow measured at stations within Kelantan watershed were collected from DID. Text data scraped from Twitter platform that contains information of selected keyword. Finally Digital Elevation Model (DEM) is used to extract parameters related to flood susceptibility analysis and mapping.

5. In line with the current National NaFFWS by DID, the forecasting targeted is 7 days in advance. Therefore, this research used daily rainfall, water level time series to forecast the next future days.

1.5 Significance and Contribution of the Study

The contribution of this research will be the theoretical justification that the new model for flood forecasting that applying different data types will produce meaningful flood prediction information to decision maker in taking precaution and making appropriate action before flood.

A multidisciplinary study in which knowledge of multiple fields is integrated to establish the effective and practical flood prediction system. The integrated knowledge will include flood disaster prevention and preparation and Artificial intelligence that involved the field of ML and NLP that is popular in computer science, together with morphometric approach that applied for developing a new flood prediction model and mapping. The output of prediction model will be display in the form of information visualization that will be able to evaluate the accuracy of the forecasting and lead time of the flood event based on the input parameters.

1.6 Thesis outline

This thesis comprises 5 chapters, which are briefly outlined below.

Chapter 1: Introduction

This chapter discusses the background of the study, problem statement, aim and objectives of the study, significance and contribution of the study.

Chapter 2: Literature Review

In this chapter, the significance of flood disaster and its negative impact to the world, the Asian region, and the selected study area are highlighted. Disaster management cycle is presented and non-structural measure is discussed as the main focus of this study. Besides, previous studies of flood prediction models using related approach and parameters are reviewed.

Chapter 3: Research Methodology

This chapter mainly discusses on research process of flood forecasting model using different data types applied for different approaches. Times series data is used to predict rainfall and water level, Long-Short Term Memory (LSTM), Autoregression integrated moving average (ARIMA), and Facebook Prophet (FB Prophet) are the models discussed for flood prediction pipeline. Text data which extracted from Twitter platform is used for text classification to classify flood events through classification algorithm such as Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR). Adopted Morphometric Ranking Approach (MRA) was discussed for the process of implementing flood susceptibility analysis and develop flood mapping.

Chapter 4: Result and discussion

Development of flood prediction model using advanced ML approach for the prediction of rainfall intensity and water level using observation data at multiple points was presented. Followed by sentiment analysis and flood event classification using text data that extracted from Twitter platform. Lastly, flood susceptibility and mapping using MRA to identify flood risk area at Kelantan watershed are presented. Models performance were compared and evaluated. Flood report from DID was used to validate flood susceptibility and mapping.

Chapter 5: Conclusion and recommendation

This chapter summarized the conclusion of each research objectives, followed by the statement of limitations and future works.

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LIST OF PUBLICATIONS

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