IOT BASED REAL-TIME MONITORING SYSTEM OF RAINFALL AND WATER LEVEL FOR FLOOD PREDICTION USING LSTM NETWORK

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# ABSTRACT

This project outlines the design of a flood monitoring system to obtain accurate data on river overflows. Additionally, it provides the machine learning technique, to predict the arrival of floods, by considering the rainfall data and water level from previously available data to predict the rainfall and water level for the next hours. The problem is the shortage of flood information in areas that are constantly flooded leads to malfunction in analysing the flood reasons. In addition, the fuzzy and unpredicted situation of the flood. Moreover, there is no flood data analysis so action can be taken based. Finally, data is not visualized in a Dashboard, so they can have a deeper look at the situation. The object of this study is to design an IoT flood monitoring system based on two water level sensors and a rain gauge sensor. In addition, to forecast the flood based on Long Short-Term Memory (LSTM) networks for historical data and the data collected from the monitoring system. The monitoring system utilizes a submersible water level sensor that measures the water level. Additionally, the tipping bucket rainfall sensor measures the rain gauge and tests the rainfall in the natural environment. The system is based on IoT to provide real-time data. The recorded data is transmitted to the cloud via a GSM network and displayed on an online platform. The flood forecasting model used Long Short-Term Memory (LSTM) networks to predict future floods. The aim of this case study is to contribute to the reduction of casualties and flood damage in streams, as well as to the development of more accurate flood forecasting in typical urban flood risk locations. The result was experimented with using historical data since the current data is insufficient yet to make an accurate prediction. The main findings of the research are the predicted values of streamflow and rainfall for historical data, also water level and rain gauge for new data. The forecasting method that applied LSTM showed high accuracy of the result reaching more than 90% with evaluation errors for historical data MAE, RMSE and MSE are 0.93, 1.7 and 3.025 respectively. Also, 0.0055, 0.3325 and 0.1175 for new data respectively. The developed monitoring system and flood forecasting can be used efficiently as a non-structural solution to alleviate the damage caused by urban floods.

# ABSTRAK

Projek ini menggariskan reka bentuk sistem pemantauan banjir untuk mendapatkan data yang tepat mengenai limpahan sungai. Selain itu, ia menyediakan teknik pembelajaran mesin, untuk meramalkan ketibaan banjir, dengan mempertimbangkan data hujan dan paras air daripada data yang tersedia sebelum ini untuk meramalkan hujan dan paras air untuk jam berikutnya. Masalahnya ialah kekurangan maklumat banjir di kawasan yang sentiasa dinaiki air menyebabkan tidak berfungsi dalam menganalisis punca banjir. Selain itu, keadaan banjir yang kabur dan tidak dijangka. Selain itu, tiada analisis data banjir jadi tindakan boleh diambil berdasarkan. Akhir sekali, data tidak divisualisasikan dalam Papan Pemuka, supaya mereka boleh melihat situasi dengan lebih mendalam. Objektif kajian ini adalah untuk mereka bentuk sistem pemantauan banjir IoT berdasarkan dua penderia aras air dan penderia tolok hujan. Di samping itu, untuk meramalkan banjir berdasarkan rangkaian Long Short-Term Memory (LSTM) untuk data sejarah dan data yang dikumpul daripada sistem pemantauan. Sistem pemantauan menggunakan sensor paras air tenggelam yang mengukur paras air. Selain itu, sensor hujan baldi tipping mengukur tolok hujan dan menguji hujan dalam persekitaran semula jadi. Sistem ini berdasarkan IoT untuk menyediakan data masa nyata. Data yang direkodkan dihantar ke awan melalui rangkaian GSM dan dipaparkan pada platform dalam talian. Model ramalan banjir menggunakan rangkaian Memori Jangka Pendek Panjang (LSTM) untuk meramal banjir akan datang. Matlamat kajian kes ini adalah untuk menyumbang kepada pengurangan mangsa dan kerosakan banjir di sungai, serta pembangunan ramalan banjir yang lebih tepat di lokasi risiko banjir bandar biasa. Hasilnya telah diuji dengan menggunakan data sejarah kerana data semasa tidak mencukupi lagi untuk membuat ramalan yang tepat. Penemuan utama penyelidikan adalah nilai ramalan aliran sungai dan hujan untuk data sejarah, juga paras air dan tolok hujan untuk data baharu. Kaedah peramalan yang menggunakan LSTM menunjukkan ketepatan keputusan yang tinggi mencecah lebih daripada 90% dengan ralat penilaian untuk data sejarah MAE, RMSE dan MSE masing-masing ialah 0.93, 1.7 dan 3.025. Juga, 0.0055, 0.3325 dan 0.1175 untuk data baharu masing-masing. Sistem pemantauan yang dibangunkan dan ramalan banjir boleh digunakan dengan cekap sebagai penyelesaian bukan struktur untuk mengurangkan kerosakan yang disebabkan oleh banjir bandar.

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| | | |
|---|---|---|
| IoT | - | Internet of Things |
| FMPS | - | Flood Monitoring and Prediction System |
| ML | - | Machine Learning |
| AI | - | Artificial Intelligence |
| QPF | - | Quantitative Precipitation Forecasting |
| SVR | - | Support Vector Regression |
| SVM | | Support Vector Machine |
| GSM | - | Global System for Mobile communications |
| LoRaWAN | - | low-power wide-area network |
| UTM | - | Universiti Teknologi Malaysia |
| JB | - | Johor Baru |
| FFNN | - | feedforward multilayer neural network |
| BP | - | Backpropagation |
| BPTT | - | Backpropagation Through Time |
| ANN | - | Artificial Neural Network |
| RNN | - | Recurrent Neural Networks |
| LSTM | - | Long Short-Term Memory Networks |
| TBRS | - | Tipping Bucket Rainfall Sensor |
| SLT | - | Submersible Level Transmitters |

# CHAPTER 1

# INTRODUCTION

The floods prediction system has been improved to guarantee that society is alerted to flood disasters with little damage. Standard management measures have been implemented to reduce the likelihood of a flood disaster occurring in a potentially at-risk location. All angles of all areas and disciplines have been called upon to collaborate in mitigating the effects of the flood calamity. Government and non-government sectors have emphasised pre-, during-, and post-flood management in an effort to lessen the flood's aftermath. This project aims to improve the timeliness and accuracy of flood prediction systems considering the significance of making a little contribution to flood. While in this chapter, it covers the background concept for this project, which has driven the development of its ideas. Moreover, the structure of this study, the problem statement, objectives, and scope of the project will be discussed.

## 1.1 Problem Background

### 1.1.1 Effects of Flood

Floods are one of the most prevalent and destructive natural dangers in the world [1] [2]. Between 1996 and 2015, the United Nations Office for Disaster Risk Reduction reports that 150,016 floods occurred, severely damaging natural systems and human activities [3]. Floods in previous years have been the most expensive calamities in terms of property damage and human losses. These floods result in significant losses and destruction, as well as catastrophic socioeconomic, hydrological, and climatic secondary repercussions [4]. For instance, in 1938, 1966, 1981, 1997, and 1998, several sections of Europe witnessed major summer floods, compromising their economic and environmental conditions [5]. More than 15.5 billion euros in damage was inflicted by the Arno River floods in Italy [6]. Between 1989 and 1999, floods in the United States claimed at least 988 lives and caused economic damages of around 4.5 billion dollars [5]. Climate change is considered to be responsible for natural catastrophes such as flooding and tropical cyclones, which are thought to be triggered by extreme weather conditions as well as changes in global and regional climate. Flooding has three distinct effects: the primary, secondary, and tertiary effects. The primary effects of floods are those experienced by individuals who come in direct contact with floodwaters. Secondary effects include disruptions to infrastructure and services, as well as health consequences, whereas tertiary effects are long-term changes that occur, such as changes in the position of river channels [7]

### 1.1.2 Effect of Flood in Malaysia

Floods are one of the most common natural disasters in Malaysia, occurring virtually every year, particularly during the monsoon season[8]. Previously, the worst flood in Malaysian history happened in 2014 [9]. More than 200,000 people were affected while 21 were killed. The major disasters happened in the several states on the east coast side of Peninsular Malaysia. The estimated cost of damages was over one billion as reported in [10]. According to [11] floods struck Pahang in January 2018, resulting in the deaths of two people and the evacuation of approximately 12,000 people. Recently, the last flood happened in 2021, floods caused by rivers flowing into the mainland have inundated many areas, ruined buildings, blocked off important highways, and affected the provision of basic services such as water, food and health care. According to [12] more than 18,000 families have affected by this flood. The climatic conditions in Malaysia and the heavy rains make it an area with a high risk of flooding. The impact of the flood is huge, and it is not happening in Malaysia but all over the world. The effects of floods could be mitigated by having a flood prediction using flood monitoring system data that allows the residents to be informed quickly and efficiently. Figure [1.1] illustrate the frequency of natural disasters that occurred in Malaysia, from 1965 to 2016.

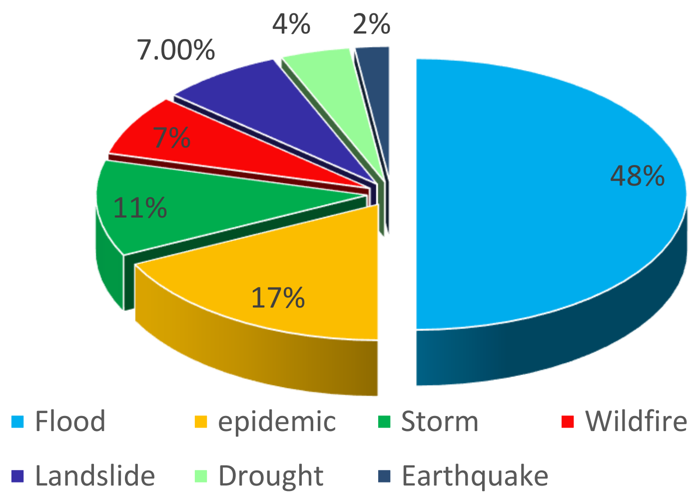


**Figure 1.1 Percentage of types of disaster in Malaysia 1965-2016[9]**

Specifically, two forms of flooding commonly occur in Malaysia, namely monsoon floods and flash floods. Monsoon flooding often occurs from May to August (Southwest Monsoon) and from November to February (Northeast Monsoon) (Northeast Monsoon) [13]. In contrast, flash floods commonly occur in urban areas. It is the result of unrestricted human activity, such as the construction of infrastructure near river regions and the disposal of rubbish, which clogs drains and waterways [14].

In the state of Johor, the Johor River basin is the primary source of drinking water for household usage, not only for the state of Johor but also for Singapore. This river basin comprises fourteen percent of Johor. The occurrence of flooding in this river basin will have severe consequences for the water supply, damage of infrastructure, and populations in the river basin's vicinity. The Northeast monsoon has the greatest impact on flooding in Johor. Changes in land use in a specific region as a result of deforestation for palm plantations influence the rate of surface runoff into the river, which may result in excessive sedimentation. This will result in alterations to the water level in the Johor River basin. If citizens in the river basin are not forewarned of the impending flood at an early stage, this circumstance might result in significant complications. A delayed emergency response plan may result in the destruction of structures and facilities, with death as the worst possible outcome [15]. During the recent floods in Johor in 2006–2007, a couple of very strong rainfall storms produced major flooding. The estimated overall cost of these flood disasters in terms of property loss was USD 0.5 billion, making it one of the most expensive flood occurrences in

Malaysian history. At the height of the recent Johor flood, around 110,000 people were evacuated and relocated to rescue shelters, and 18 people perished [16].

## 1.2 Internet of Things (IoT)

The Internet of Things (IoT) refers to the connection of physical devices, cars, buildings, and other items embedded with electronics, sensors, actuators, communication protocols, and software that collect, share, store, analyse, and process data [17]. Experts estimate that the number of IoT devices worldwide is forecast to almost triple from 8.74 billion in 2020 to more than 25.4 billion IoT devices in 2030 [18]. According to most researchers, IoT architecture consists of five levels. Figure [1.2] illustrates the conventional IoT architecture[19].

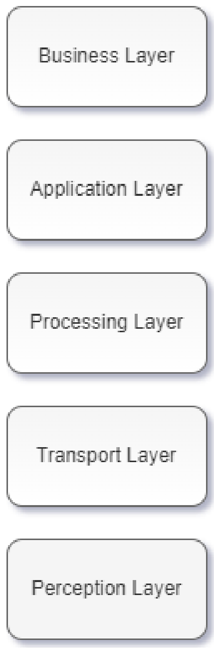


**Figure 1.2 Five-layer architecture of IoT**

The perception layer is the physical layer, which contains sensors, actuators, and edge devices that interact with the environment. Some physical parameters are sensed in the surroundings, and other intelligent items are discovered. The transport layer transfers sensor data from the perception layer to the processing layer and vice versa through networks such as GSM, Bluetooth, Wi-Fi, LAN, and Lora WAN etc.

The processing layer is also referred to as the middleware layer. the large data sets are analysed, stored, and processed. Databases, cloud computing, and large data processing resources may be used. The application layer is responsible for providing the user with specific application services. It defines several IoT applications, including smart homes, smart cities, and intelligent health. The entire IoT system is managed by the business layer, including applications, business and business models, and user privacy.

### 1.2.1 IoT Elements

The structure of IoT, shown in Figure [1.30], is based on five main components which are the things or device (sensor nodes), field getaway, cloud, storage and analytic [20].

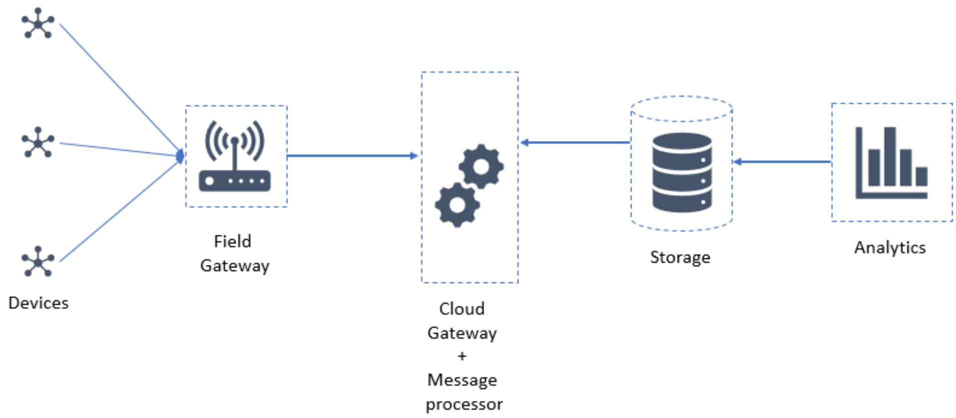


**Figure 1.3 IoT elements**

The term "thing" refers to any device or sensor equipped with an embedded system capable of connecting to the Internet. They are low-power sensors that detect a single object. Such as water level, Temperature, GPS location, and motion. These devices, or sensors, are constantly collecting data from their surroundings and passing it to the next layer via low-power wireless networks such as GSM, Wi-Fi, Bluetooth, LoRAWAN and Z-wave etc.

Field gateways, or gateways, are intelligent devices that serve as a connection point between sensors and the cloud. It enables IoT connectivity and data transmission in both directions between networks and protocols. This is necessary because the sensors are small/low-power devices and transmitting data via a wire consumes a lot of electricity. As a result, gateways are required to conduct this function on the sensor's behalf. Additionally, the gateway may translate several network protocols and assure device and sensor interoperability. Additionally, it stores, and pre-processes data acquired from thousands of sensors on-premises prior to uploading it to the cloud.

The cloud gateway is the most critical component of the Internet of Things system. It serves as the cloud gateway for messages sent by devices. This is the point of entry for the IoT system. Its responsibility is to aggregate and manage massive processing data in real-time, then store it for analysis over time. Generally, it does not process data. Users can simply gain remote access to this data and make critical decisions as needed.

Message processor: The data collected from various devices are decoded, filtered according to their characteristics, processed for information retrieval, and finally stored in a structured manner. Typically, this component is developed on a case-by-case basis in accordance with the needs.

Storage is the place to save the messages/data after processing and filtering. The results in this section are derived from data collected from devices. The incoming data will be analyzed using a data analytics engine to find patterns and abnormalities. This can also be a component of machine learning. Essentially, all the data we received and processed in the earlier steps are being used.

Monitoring Dashboard: Finally, the result accomplished is needed to showcase in a structured manner by reporting component. This might be a basic excel sheet with some charts or it can be a standalone business intelligence dashboard.

## 1.3 Machin Learning and Deep Learning

Machine learning (ML) is a subfield of artificial intelligence (AI) that is used to infer regularities and patterns. It enables easier implementation with low computation costs, as well as fast training, testing, validation and evaluation while maintaining high performance in comparison to physical models [21]. Fundamentally, machine learning involves the use of algorithms to extract information from unprocessed data and describe it using a model. We utilize this model to make inferences about data that has not yet been modelled. Neural networks are one sort of machine learning model that has existed for at least fifty years. A node, which is loosely based on the biological neuron in the human brain, is the fundamental unit of a neural network. The connections between neurons are also modelled after actual brains. In the early 2000s, computer power grew tremendously, and the industry witnessed a "Cambrian explosion" of previously impossible computational approaches. Deep learning developed as a strong contender in the industry as a result of the decade's tremendous rise in processing power, winning several significant machine learning contests. The field of AI is broad and has been around for a long time. Deep learning is a subset of the field of machine learning, which is a subfield of AI as shown in Figure [1.4] [22].

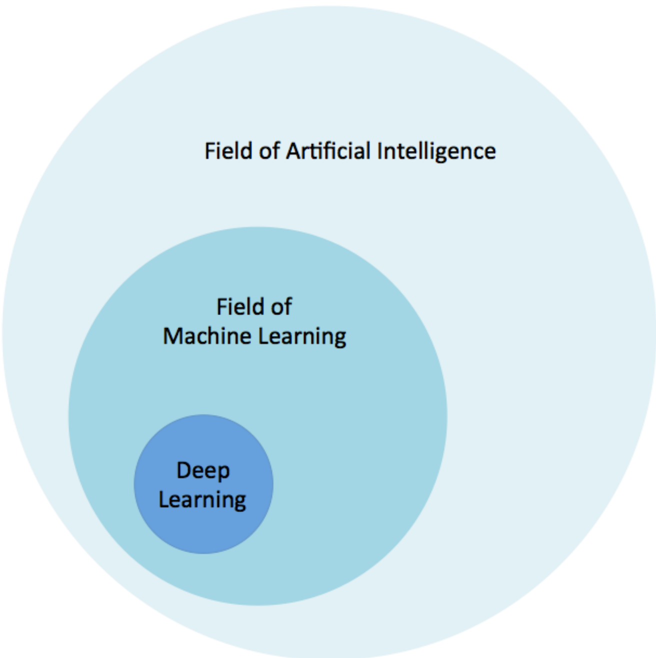


**Figure 1.4 The relationship between AI and deep learning**

Machine learning algorithms can either be supervised or unsupervised. The difference between these two main classes is the existence of labels in the training data subset as shown in Figure [1.5]. According to [23], supervised machine learning involves predetermined output attributes besides the use of input attributes. The algorithms try to forecast and classify the specified attribute, and their accuracies and misclassifications, in addition to other performance metrics, are reliant on the counts of the predetermined attribute that have been successfully predicted or categorized or not. It is also essential to note that the learning process concludes when the algorithm reaches a satisfactory level of performance [24]. Technically, according to [25], supervised algorithms execute analytical tasks using training data before constructing contingent functions for mapping new occurrences of the characteristic. The methods for supervised learning are further divided into classification and regression algorithms [24].

In contrast, unsupervised learning includes the detection of patterns without a desired characteristic. Due to the strategy and the fact that all variables utilized in the study are inputs, the approaches are ideal for clustering. According to [26], unsupervised learning algorithms are appropriate for labelling the data, which is then used to complete supervised learning tasks. In other words, unsupervised clustering algorithms find intrinsic groups within unlabeled data and then label each data value [24]. Unsupervised association mining algorithms, on the other hand, have a tendency to identify rules that properly describe associations between characteristics.

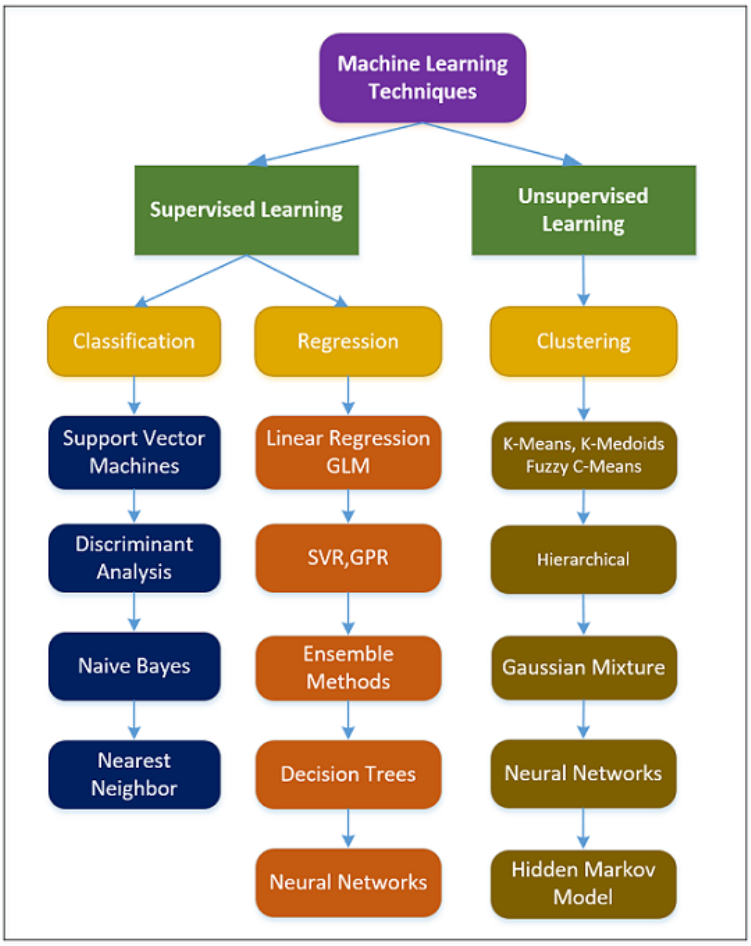


**Figure 1.5 Machine learning techniques**

## 1.4 Problem Statement

Flash floods and other flood-related disasters are becoming a common source of human loss and property damage in Malaysia. As a result, damage will happen to public buildings, roads, and cabling systems. More vehicles will be stuck in traffic, which will lead to more delays in public transportation and an increased risk of traffic collisions and other accidents and so on. Based on that, we can list our problem statement as four main points. First of all, the shortage of flood information in areas that are constantly flooded leads to malfunction in analyzing the flood reasons. Secondly, the fuzzy and unpredicted situation of the flood. Moreover, there is no flood data analysis so action can be taken based. Finally, data is not visualized in a Dashboard, so they can have a deeper look at the situation.

## 1.5 Research Objectives

a) To design an IoT flood monitoring system based on two water level sensors and rain gauge sensor
b) To forecast the flood based on Long Short-Term Memory (LSTM) networks for historical data and the data collected from the monitoring system

## 1.6 Research Scope

This study presents a flood forecasting and warning method based on two different datasets and a deep learning technique to prevent casualties in an urban stream from urban flash floods and reduce urban flood damages. the first dataset (historical data) is collected from hydrological stations in JB at three different stations between the 1st of June 2010 and until 1st of Dec 2012. The historical data is two Rainfall data and one streamflow data. The second dataset is collected from the designed IoT monitoring system for one month (10th of May until 11th of June 2022). the data collected from UTM campus is with two submersible water level sensors and one rain gauge which is the tipping bucket rainfall sensor. The collected data is transmitted to the cloud by GSM network and then displayed by using a developed platform/dashboard to show sensors' data.

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