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Earthquake Prediction Based on Machine Learning Techniques

A Thesis

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By

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بسم الله الرحمن الرحيم

اقْرَأْ بِاسْمِ رَبِّكَ الَّذِي خَلَقَ ﴿١﴾ خَلَقَ
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Dedication

Firstly, I will dedicate this thesis to our Almighty Allah, who gives his strength and knowledge for my everyday life.

To my parents

I was hoping that they would be alive today to share me in the celebration and the success of my graduation with a master's degree.

To my friendly brothers and my uncle and aunts and everyone who stood by me

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Supervisor Certification

*I certify that this thesis entitled "***Earthquake Prediction Based on Machine Learning Techniques***" was prepared under my supervision at the department of computer science – College of Computer and Information Technology– Anbar University, by "* **Abrar Khalid Saleem***" as partial fulfillment of the requirements of the degree of Master of Science in Computer Science.*

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Linguist Certificate

*I certify that, I read this thesis entitled (**Earthquake Prediction Based on Machine Learning Techniques**) and I found it linguistically adequate.*

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ABSTRACT

Earthquakes are a natural calamity produced by the movement of the earth's tectonic plates due to enormous internal energy being released, earthquakes can cause in serious injuries and fatalities, demolish massive structures and infrastructure leading to significant economic loss. Earthquakes predictions are achieving society's safety, reduce the magnitude of destruction. For predicting an earthquake's time, magnitude, depth, and location, a variety of techniques have been suggested, such as statistical and mathematical analysis and a signal investigation of precursors and due to an ostensibly dynamic character of seismic, they usually do not produce excellent results. The ability of artificial intelligence to detect hidden patterns of data and nonlinear relation well-known has been gaining attention in recent years. It has been used in several areas and achieved positive results. This thesis utilizes artificial intelligence algorithms in predicting the next earthquakes to take the necessary precautions and reduce the risk in earthquake-prone areas. The support vector regression, feed-forward neural network and long short-term memory algorithm were applied to predict the occurrence of the next earthquake based on the historical data obtained from the General Directorate of Meteorology and Earthquake Monitoring in Iraq, through study data for three different regions in Iraq (Sulaymaniyah, Maysan and Wasit) to predict earthquake characteristics (time, magnitude, location and depth) and evaluating the performance of the prediction using testing data

The obtained results are compared by evaluation metrics to show which algorithm is the best for earthquake prediction. From these results, it is concluded that the long short term memory is the best for earthquake prediction and assists in obtaining promising results, because Long Short Term Memory is an optimized neural network that can handle issues of exploding and vanishing gradients. This algorithm where achieved 87% accuracy in predicting the time and magnitude of the earthquake, 88% accuracy in predicting time, magnitude, and location of the earthquake, and 91% accuracy in predicting the magnitude, location, time and depth of the earthquake.

Keywords: Earthquake prediction, artificial intelligence, machine learning, deep learning, support vector regression, feed-forward neural network, long short term memory, regression system.

List of content

List of Tables

List of Figures

List of Abbreviations

Abbreviations	Meaning
AI	Artificial Intelligence
ANN	Artificial Neural Network
BPNN	Back Propagation Neural Network
BPTT	Back Propagation Through Time
DL	Deep Learning
DNN	Deep Neural Network
FFNN	Feed Forward Neural Network
FLANN	Functional Link Artificial Neural Network
GA	Genetic Algorithm
GIS	Geographical Information System
LM	Levenberg-Marquardt
LSTM	Long Short Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
NN	Neural Network
PSO	Particle Swarm Optimization

RBF	Radial Basis Function
RF	Random forest
RMSE	Root Mean Square Error
RMSprop	Root Mean Square prop
RNN	Recurrent Neural Network
SVM	Support Vector Machine
SVR	Support Vector Regression
DtMg	Prediction of Time and Magnitude are Correct
Dt	Prediction of Time is Correct
Mg	Prediction of Magnitude is Correct
I	Prediction of Earthquake Characteristics are Incorrect

CHAPTER ONE

Introduction

CHAPTER ONE

1. 1 Introduction

Earthquake is one of nature's most devastating disaster. They usually happen without warning. A major earthquake with a magnitude greater than five can inflict massive death tolls and huge infrastructural damages.

The earthquakes prediction is a very important, the success of which may potentially save many human lives. However, it has been that it is a challenging issue in seismology [1]. Existing works on earthquake prediction can be mainly classified into four categories according to the employed methodologies, i.e.,1) mathematical analysis, 2) precursor signal investigation, 3) machine learning algorithms like decision trees and support vector machines, and 4) deep learning. The first kind of research attempt to formulate a problem of earthquake prediction by using different mathematical tools [2], like the FDL "Fibonacci, Dual and Lucas" method, types of probability distributions or other mathematics proving and spatial connection theory [3]. In the second kind of work, researchers study earthquake precursor signals to help with earthquake prediction. For example, electromagnetic signals [4], lithosphere-atmosphere-ionosphere [5].Even animals' abnormal behavior has been taken into account in this kind of study [6]. The third kind of research is mainly explores data mining and time series analysis using machine learning algorithms, such as AdaBoost, J48, k-nearest neighbors [7], artificial neural network, and SVM [8], to forecast a magnitude of earthquakes based on the seismic events of prior. Algorithms of deep learning are used in the fourth kind of researches to forecast the time and magnitude of seismic events. Various kind of neural network have been adopted, such as feed-forward neural network, backward propagation (BP) neural network, multi-layer perceptron [9], recurrent neural network [10], which be effective in certain circumstances.

The earthquake prediction models perform well with earthquakes having medium magnitudes, but while the shocks have high magnitude, the outcomes achieved are poor. Major earthquakes cause most damages and bring the most concern. The reason behind this scenario is that there is a smaller number of earthquakes with high magnitude, and without data, the prediction becomes very difficult. Historical data from earthquake catalogs are used in forecasting studies, earthquake data characteristics in the catalogs varies from one catalog to another according to the region, but the main characteristics of an earthquake are:

- the date and time of an event.
- the epicenter's geographic coordinates.
- depth of a hypocenter.
- magnitude of the earthquake.

Other characteristics include earthquake energy, depth, location, and magnitude. Seismic indices such as Gutenberg Richter B value, seismic energy, time lag, mean magnitude [11], and others, are computed using machine learning methods. Alternatively, deep learning models are capable of calculating hundreds of complicated characteristics on their own[12][13].

1. 2 Literature Review

Earthquake prediction is one of the important issues, as it leads to saving lives and reducing losses. It is a random, destructive natural phenomenon. Studies have recently tended to predict earthquakes using learning techniques. Machine learning, and deep learning algorithms was used in many research to prediction earthquakes in the literature, summarized below:

In 2016, Narayanakumar and Raja [14], suggested the BPNN model for earthquake magnitude prediction of India's Himalayan area. They utilized eight seismicity indicators, which were computed using the Gutenberg-Richter equation from the earthquake catalog. The Global Hypocenter database was used to gather data for this study, which included earthquakes with magnitudes greater than 2.5. They utilized a neural network with nine input neurons. a twelve-neuron hidden layer and a single-neuron output layer, with Purelin and Tan-Sigmoid, were chosen as activation functions. They used the LM method to train the model across 10, 000 iterations, the learn rate start was set to 0. 01, and momentum at 0. 94. Model accuracy in predicting small earthquakes was 66.66%, and the moderate earthquake was 75%. The model was unable to forecast big quakes because there was so few training data for earthquakes with magnitudes larger than5.8.

In 2017, Zhou et al [15], suggested ANN and SVR models forecast the magnitude of the earthquake. They demonstrated that when these two algorithms were combined, performed better than when they were used alone. Gathered data from around the world between 1999 and 2016, using latitude, focal depth, and longitude, as input parameters and magnitude as an output parameter. They used a linear kernel to train the SVM model, and the violation's cost function was set to 10. They also trained a NN based on error back propagation. with 5000 epochs. The result showed that if the ratio of error is less than 0.5, the SVM model can predict correctly 9 from 15 samples, ANN was able to predict 10 of the 15 samples testing, 11 out of 15 samples could be predicted with this combination of SVR and ANN 73. 37% accuracy.

In 2017, Wang et al [16], proposed the LSTM model to forecast earthquakes, using spatial and temporal correlation. Memory-cells are used in LSTM that aid in the prediction of long-term events. They utilized a dataset from China and split the area into sub-divisions of equal sizes. In this study, a selected earthquakes dataset with a magnitude above 4.5 from 1966 to 2016, was gathered. Data of earthquakes with the same timestamp but various places were represented using a two-dimensional matrix to achieve temporal and spatial correlation, this matrix was utilized as the input for the layer of LSTM, to avoid an overfitting problem, the output of LSTM layer was sent to dropout layer and passed to a layer of fully connected, output processed using the activation function softmax, Cross-entropy was the function of error that they utilized and RMSprop algorithm as optimizer. The accuracy of the model of 86%.

In 2017, Asim et al [17], tried to assess performances of the algorithms RF, pattern recognition NN, linear programming boost, and RNN, in forecasting earthquakes with a magnitude greater than 5.4, they utilized an earthquakes dataset of the Hindu Kush area from 1976 to 2013. The PRNN trained with LM-BP as it is faster than BP and has two hidden layers, each of which had 12 neurons, tan -sigmoid was used as activation function. RNN algorithm can store an internal state, due to the fact that there are cycles directed between units, it is made up of two hidden layers, has six and seven neurons, respectively. RF algorithm consisted of a collection of a decision tree that was combined using Bootstrap bagging or aggregation. The LPBoost ensemble maximized the difference between training data from the different classes and added numerous tree classifiers. The algorithm of LP Boost performed best of 65% accuracy, while RNN achieve 64% accuracy.

In 2017, Saba S, Ahsan F, et al [18], proposed the BAT-ANN combining algorithm of Bat and feed-forward NN, to forecast the next earthquake, Back Propagation in the neural network operates on the gradient descent concept and can suffer from overfitting and becoming stuck in the local optimum. Bat algorithm develops to discover the best or near-best solution. FFNN is trained using the bat algorithm to get the best weights, used log sigmoid as a transfer function, and learning rate set to 0. 3, with 100 iterations. In terms of accuracy, the results demonstrate that BAT-ANN outperforms the Back Propagation NN.

In 2018, Lin et al [19], Attempts were made to determine the proper number of neurons in a BPNN's hidden layers for earthquakes prediction. They built the model using data from the Philippines. They used two hidden layers, and data from 2000 to 2010 to construct the first magnitude prediction BPNN model. With the learning rate of 0.83 and ten neurons in the hidden layers, the best prediction was made. Then they used the method of embedded BPNN with the same initial weights of the prior method. Data from the years 1990 to 1999 and 2011 to 2014 were used to train it. The first BPNN was then trained with data from 1990 to 2014 with a learning rate of 0.33, yielding results that were comparable to the prior model. To assess the approaches, they evaluated the standard deviation, MSE, and correlation coefficient for the anticipated and actual magnitudes of the embedded BPNN model to estimate magnitude after determining the optimal number of neurons in the hidden layers, achieved the rate of MSE of 0. 01 to 0. 09, with an average of the standard deviation equal to 0. 21.

In 2018, Hajikhodaverdikhan, et al [20], proposed an SVR method enhanced by using a particle filter to predict the number of earthquakes and mean magnitude in Iran. For this study, they evaluated 30 precursors. In SVR, the model looks to a hyperplane which could separate the dataset into subsets depending on classifications. In the presentation of noise, particle filters assess a linear system's state and converted it to randomness. The model's generalization diminishes as the C value rises, while the model's error performance rises. Indicates a loss function that has lower values is desirable; nevertheless, if it's zero, overfitting may be happening. In this model, the kernel filter was Gaussian RBF. The particle filter was used to choose these three parameters by computing the probability density function using the particle weights. PSO improved the parameter of the kernel width, C, to enhance SVR performance. The result of a PSO-based SVR model was best this method was more effective than the standard MLP method.

In 2019, Bhandarkar et al [21], suggested an LSTM model for forecasting the future trend of seismic, in this study 5000 samples were collected from Tajikistan and Afghanistan, a dataset of North-East India, Lakshadweep, and Thailand were also gathered, the LSTM model having two hidden layers, each LSTM cell has 40 hidden units, the BP was restricted to fifteen steps and used the drop out layer between two hidden layers. The algorithm of degrading was used to minimize the RMS loss. The LSTM model uses the structure's cycles to identify the sequence's dynamics. LSTM method removed the effect of the vanishing problem from the RNN and achieved good results.

In 2019, M. Maya, W. Yu [22], suggested the transfer and meta-learning for improving MLP model for earthquake short-term prediction, in the neural network, meta-learning and transfer learning are capable increase speed up convergences and give greater flexibility for model parameters. Trained a simple MLP that consisted of 10 neurons in the hidden layer, one outer-layer, and a learning rate of 0. 155, was proved to be unbalanced, by using MLP and Meta-Learning with only 100 iterations, for the same prediction. This time, it performed better than the preceding MLP, transfer learning and meta-learning were combined to increase MLP performance, the MLP-meta learn model achieved MSE from 0 to 0. 09 and with MLP-meta -transfer learning MSE of 0 to 0. 07.

In 2020, Jena, biswajeet et al [23], proposed the convolutional neural network and GIS, to study the probability of an earthquake using nine seismic features, namely, magnitude density, peak ground acceleration, epicenter density, slope angle, proximity to faults, the distance between the epicenter and the location, fault density, amplification factor value with lithology, were used as inputs, in the meanwhile, the outputs 0, 1 were utilized to represent non-seismic and seismic parameters. The proposed categorization model was evaluated on the nation level using data acquired to update a map of probability for the subcontinent of India, according to the testing data, the results showed that the suggested method outperformed established techniques for estimating earthquake likelihood, in terms of precision.

In 2020, Majhi et al [24], developed researchers a functional link ANN improved using the algorithm of moth flame optimization to forecast the magnitude of the earthquake, no hidden layer in the FLANN, nonlinearity is obtained by some nonlinear function. Standard BP, Gradient descent, LM-BP, least-square optimization, and MFO were used as learning algorithms to discover which one performs best. The model's optimum weights were determined using these algorithms. First, earthquakes data having a magnitude equal to or more than 5.5 was chosen. The date and time elements were then combined into one property. The features are all normalized. Five seismicity indicators compute, after that, 7 distinct nonlinear functions were used to extend. Finally, use them with the model to train. The model achieved a good result where the RMSE of 0. 0565 compared to IPSO-BPNN model RMSE of 0.0590.

1. 3 Problem Statements

Since earthquakes are one of the most dangerous natural disasters, primarily due to the fact that they often occur without an explicit warning, leaving no time to react. This fact makes the problem of earthquake prediction extremely important for the safety of humankind. A variety of techniques, such as statistical and mathematical analysis, have been used to predict earthquakes, but they have not given accurate results due to the non-linear relationship of earthquake data. Machine learning and deep learning techniques have been successful in many areas and have been used in earthquake prediction in many studies. However, these studies were not comprehensive in predicting all earthquake characteristics, it was limited to data with a certain earthquake magnitude and did not achieve sufficient accuracy.

1. 4 Thesis Objectives

The main objectives of this thesis can be listed as follows:

1. Building a system for earthquake prediction with high performance leads to the reduction or absence of human and material losses by taking preventive measures in areas most prone to earthquakes.
2. Applying algorithms of machine learning (FFNN) ,(SVR) and deep learning (LSTM) to predict earthquake characteristics (time, magnitude, location, and depth) on earthquake datasets for three different regions with earthquake magnitude ranging from (2.5 to 6) and evaluate their performance and compares their results with previous researches to determine its effectiveness based on metrics such as Accuracy and MSE to determine which is the best algorithm for earthquake prediction.

1. 5 Thesis Structure

This thesis consists of five chapters. **Chapter one** produces the introduction of the thesis including, literature review, problem statements, and thesis objectives. The remainder of the thesis is organized as follows:

Chapter Two: " ***Theoretical Background*** " presents the concepts of the earthquakes, how are earthquakes formed, types of earthquakes according to the depth, earthquake measurement. Also includes the concept of the neural network, machine learning, deep learning, and FFNN, LSTM algorithm.

Chapter Three*: " Research Methodology* " this chapter explains the proposed system FFNN, LSTM in a detailed description.

Chapter Four: " ***Results and Discussion*** " presents the application and results obtained when implementing the proposed system and discussing it. A comparison between results of algorithms and with results of other literature.

Chapter Five: " ***Conclusion and Future Works*** " provides a conclusion of the thesis and some recommendations for further research.

CHAPTER TWO

Theoretical Background

CHAPTER TWO

2. 1 Introduction

Earthquakes are a natural phenomenon that occurs in the ground and is caused by the movement of the rocky plates; the effect of the earthquake extends to the surface of the earth and results in the occurrence of vibrations and thus cracking in the internal rocks and this, in turn, causes the displacement of those rocks due to the geological effects and thus the fissures in the ground. Despite the possibility of earthquakes occurring at any point on the globe, their distribution is not random. Rather, it is concentrated in belts called seismic belts, among the most important of these packages:

Pacific belt (70%)

Alpine belt (20%)

These two belts include 90% of the earthquakes that occur on the ground and these two belts branch out from small belts that are less effective than the main ones. The earthquakes that occur in the Arab regions, which extend from the Strait of Gibraltar - the Alps - the Taurus Mountains in Turkey - the Zagros Mountains in Iraq and Iran - the Himalayas and Southeast Asia are within the alpine belt.

The geographical distribution of these belts depends on the theory of plate tectonics, according to which assume that the outer part of the globe is divided into several different plates and there is a relative movement between these plates that is convergent, divergent or transitional movement so earthquakes are concentrated in the border regions of the plates and in their midst these plates Collision leads to diving one to edge of plate anther where rupture occurs of the earth's crust[25].

This chapter presents a description of the earthquake, how are earthquakes formed, types, earthquake measurement and earthquake prediction techniques as well as machine learning techniques, deep learning.

2. 2 Earthquake Brief

It is the shaking of the earth caused by the rapid and sudden release of energy that accompanies the breaking of rocks. The main source of energy is the movement of the plates, the epicenter of the earthquake (the focus) is followed by aftershocks called Seismic waves, and this is due to the breaking and displacement of rocks due to the accumulation of internal jurisprudence as a result of influences Geology resulting in the movement of the earth's plates, and the earthquake may arise as a result of volcanic activities or as a result of because there are slips in the layers of the earth, earthquakes lead to cracking of the ground and the depletion of springs or the occurrence of elevations and depressions in the earth's crust, as well as the occurrence of high waves under the sea surface (tsunami)[26].

As well as its devastating effects on buildings and facilities and often results from convective movements resulting from asthenosphere (in which the near-plates move, causing tremors) earthquake. Also, earthquakes may cause havoc. The degree of earthquakes is determined by an index and is measured from (10) degrees Richter. From (1-4) earthquake degrees, which may not cause any damage, that is, it can only be felt, from (4-6) earthquake average damages. Damage to homes and residences may occur. From 7 to 10 (maximum degree, that is, the earthquake can destroy an entire city and put it underground, often the mainshock is preceded by a few days or even years of light tremors called the foreshock. As for the tremors that follow as a result of the crumbs rock is called tremors (aftershock).

2. 3 Earthquake Description

During the vibration that hits the cortex, six kinds of shock waves are generated two are related to the body of the earth, as they affect the interior of the earth, while the other four waves are surface waves and can be distinguished through the type of movements that affect, on the rock particles, where the primary waves or pressure waves send particles that vibrate back and forth in the direction of the waves while secondary or transverse waves reduce vibrations perpendicular to the direction of its course. Usually, the primary waves travel faster than the secondary waves, so that's when it happens earthquake, the first waves that arrive and are recorded in geophysical research stations all over the world are primary and secondary waves[27].

2. 3. 1 Types of Earthquakes According to The Depth

- Shallow earthquakes being a depth of 70 km.
- Medium earthquakes being a depth of 70-300 km.
- Deep earthquakes are the depth at 300-700 km [28].

2. 3. 2 The Intensity and Magnitude of Earthquake:

Scientists use the concepts of earthquake intensity and earthquake magnitude to express the magnitude of an earthquake. Earthquake magnitude is a term used to measure the magnitude produced by an earthquake Richter's ten degrees. The intensity of the earthquake varies from one region to another, but the magnitude of the earthquake is fixed[29].

2. 3. 3 Earthquake Measurement

Earthquakes vary among themselves in the amount of damage and losses they inflict and this is controlled by several factors. Including the distance to the earthquake epicenter, the nature of the earth's crust rocks, the designs of the buildings, and the area in which it occurred is the earthquake populated or not? The reliance in the study of earthquakes was previously on a description intensity (i. e. The amount of damage it causes).

Later, a new scale was developed to classify earthquakes based on the amount of energy released at the earthquake occurred. In the year 1935, Charles Richter introduced a seismometer based on estimating the strength of the energy released from it by measuring the largest amplitude of the waves recorded on the seismograph.

depending on. Represents by Eq.(2. 1).

$$M = \log (A / t + y) \qquad (2.\ 1)$$

Where: A = the largest displacement, measured in units, each of which is from 4-10 cm, t is equal to the time it takes to record seismic waves in seconds and y is equal to the distance adjustment factor and calculate using the difference in the arrival time between primary and secondary waves [30].

2. 3. 4 Determine the location of an earthquake focus

The earthquake epicenter is the site from which the energy emission begins and because tremors occur as a result of movement on both sides of a crack the focus of the earthquake is not a point, but rather an area that can extend for a few kilometers. The earthquake is at varying depths from the surface of the earth to a depth of 700 km. So it is appropriate to talk about the location of the epicenter of earthquake on the earth's surface, called the epicenter of the earthquake the vertical distance between the epicenter of an earthquake and the point on earth's surface directly above it at depth, focal depth the location of a seismic focus can be determined by the cooperation of three seismic stations close to the location of the earthquake and the earthquake's distance from each of these three stations is determined either by the relationship data or by calculating the distance by estimating the time of arrival of seismic waves and their speed (Distance = time * speed of the waves) and a circle is drawn from each station whose center is the location of the station, its radius is the calculated distance and the point of intersection of three circles is the epicenter of the earthquake[31].

2. 4 Earthquake Prediction Techniques

Despite the fact that the terms "forecast", "prediction" are frequently interchanged, it is common in earthquakes science to separate them. In[32]The concept was articulated that the earthquakes prediction suggests a higher likelihood than the earthquakes forecast; that is to say, the prediction is more certain than the forecast, and thus necessitates greater precision. So, it's worth mentioning that the focus of this thesis will be on earthquake prediction, which appears to be more significant from a practical standpoint. According to[33] follows information is needed from predicting the earthquake: define the time of earthquake; define the magnitude of the earthquake; define the location of the earthquake. Furthermore, if the prediction provides the likelihood that the event that fulfills all of the aforementioned conditions occurs, it is more valuable and verified statistically[34]. That is, the prediction should state when, where, and the magnitude of the earthquake, as well as how likely it will happen in reality.

there are many of techniques learning used for earthquakes prediction (time, location, magnitude) such as machine learning algorithms, random forest, support vector regression, support vector machine, artificial neural network, K-nearest neighbor, clustering, probabilistic neural network.

The deep learning algorithm, recurrent neural network, deep neural network, long short-term memory[35].

2. 5 Artificial Neural Network

The artificial neural network is a model of the nervous system that is inspired from reality, its studies are compatible with several disciplines in various fields growing and it is considered an adaptable, often non-linear distributed system, these three elements are present in real applications. Neural networks have become used in many a variety of important fields such as science and engineering as noise cancellation, system identification, prediction, signal enhancement. They're also found in a variety of commercial goods, including modems, biomedical equipment, image processing systems, and voice, speech recognition systems. A new area of computational science that incorporates many techniques for problem resolution that are difficult to define without the algorithmic focus, these approaches are based on the simulation, more or less intelligent, of biological systems' activity in some way. Artificial intelligence is a new type of computing denominated, that through a variety of approaches, is capable of handling the uncertainties and imprecisions that arise while attempting to solve issues in the real world, while still providing a solid solution that is simple to apply. Artificial neural networks are one of these approaches, which are inspired by the human brain's functioning and these are a collection of a large number of process elements–interconnected artificial neurons that solve the problem by working in parallel[36]. There are several ways to define what NN is, ranging from brief and general definitions to those that attempt to describe in-depth what a neural computing or neural network the definition provided by Teuvo Kohonen[37]is as follows:

" Artificial Neural Networks are massively interconnected networks parallel of simple elements (usually adaptable), with hierarchic organization, which try to interact with the objects of the real world in the same way that the biological nervous system does".

The comprehend of artificial equivalent for neuron, known as a node or computational neuron, as a basic element. These are arranged by layers in a hierarchical structure and are interconnected amongst them, exactly like systems of biological nerves. The artificial network arises in response to the presence of an external stimulus corresponding to reality and therefore to determine appropriate modification in the internal parameters of the network. This modification is called a training or learning network, so that the network is then able to respond to a stimulus external in an optimal manner.

2. 5. 1 Artificial Neural Network Applications

In terms of the applications, can say that the artificial neural networks' strengths are in the management of adaptive, parallel, and nonlinear processes. Computer vision, speech recognition, medical image analysis, expert systems, remote sensing, signal processing, and industrial inspection have seen success with the ANN. Artificial neural network applications are divided into the following types:

Pattern recognition: Is assign the class label to an item represented by a vector in a predetermined of classes, (supervised classification).

Grouping: Is known as unsupervised categorization since there is no predetermined classes. The network checks the items in front of them and groups together features that match certain criteria for similarity.

Approximation of functions: In a collection of the pairs (ordered pairs for /entry, exit), a network modifies the internal parameters to construct exits that correspond implicitly to the function's approximation.

Prediction: Predict the behavior of the event that is time-dependent, based on a set of data acquired at various times.

Optimization: wide range of issues in science, engineering, medicine, and math can be focusable as problems requiring the determination solution that satisfies a set of constraints while minimizing or maximizing the objective function.

Association: Associative formulations can be divided into two categories, self-association, and hetero. -association, in self-association issues, whole knowledge is retrieved from partial information. Given the element from the group of A, hetero-association consists of retrieving the element from the group of B.[37].

2. 5. 2 Topology of Neural Network

Architecture, topology, or structure are terms used to describe how computation neurons are structured in a network. These words are most commonly used to describe how nodes are communication, how data is transferred across a network, distribution of computation neurons.

The number of layers: The neurons in neural nets do by constructing layers or levels with a specific number of nodes. As long as there are inputs, hidden neurons, and outputs, can define the inputs layer, the outputs layer as well as one or more hidden layers. Some authors considered only two types of layers in the ANN, a hidden and an output layer.

Patterns of connection: ANN may be categorized into the following connection patterns based on the linkages between items of various layers when all of a level's outputs reach all and each of nodes in the next layer, it is said to be completely connected, while if network lost some of it connection, network is said to be partly connected.

Information flow: Another categorization of ANN is determined by a direction of information flow across the layers, connection between the nodes is a way that outputs of a neuron are directed to be input to other neurons. A node's output signal might be one of a process's entries, network is defined as feed-forward network. While any of the neurons' outputs are input to neurons at the same level or levels above it if at least one is an entry of neurons from prior levels, the network is defined as a feedback network[38].

2. 6 Learning Processes

The capacity to learn is a key feature of all neural networks model, as evidenced by the fact that their performance improves as a result of learning and occurs as a result of an interactive process that modifies the parameters of the network in response to external stimuli. Ideally, ANN learns more with each iteration of a process learning. offering definition for learning term can being adventurous, the vast array of fields of human knowledge that are involved its study, this text does not claim to cover in-depth, can define learning in general as the change of behavior result of the experience. In this light, Mendel and

McClaren (Haykin)[37].In the domain of artificial neural networks, defines utterance learning as follows:

"Learning is a process by which, the free parameters from a neural network are adapted, through a simulation process, by the environment in which a network is contained. The kind of learning is determined by the way in which the change of the parameter has place ".

This definition means a sequence of events that follows:

- The network's environment serves as a simulation of the network.
- The neural network's internal parameters are modified as the result of simulation, a set of rules governs these modifications.
- The changes in the internal structure of the neural network cause the neural network to respond properly.

It's worth noting that a learning rule or an algorithm refers to a set of rules that make up a learning process. Additionally, internal parameters are utilized to create a set of communication linkages between computation neurons. The weight, to put it another way, A neural network's training or learning consists basically of modifying the weights of the network. Utilizing learning algorithms.

There is no one-size-fits-all learning algorithm for neural networks. Learning algorithms are divided into two categories: supervised learning and unsupervised learning, based on the paradigm employed.

2. 6. 1 Supervised Learning

As stated that learning algorithms are capable of using supervised learning and unsupervised learning, in this work emphasis will be based on the learning system which is by supervision, particularly for regression. In the supervised model of learning, feedback is given for the system to carry process learn, the training set is the general selection for feedback that is used to apply to learn the supervised system. The training set contains a different set of an example that include values of input and outputs. These examples are for internalizing and use as a base for learning dynamic of mapping of the various inputs to their matching on the right output the learning machine's phase. At the execution stage, a set of new inputs are given to the system to predict the outputs using knowledge obtained while learning. The process of putting previously learned knowledge to use on new data is referred to as generalization. The accuracy of the generalization is calculated usually by using a test set when the system makes a prediction, the accuracy of outputs produced by algorithms can be calculated easily by contrasting the prediction results of the algorithm with actual results. There are a large of available learning models which may be used to solve the problems by supervised learning, such as the neural networks. These models have a set of benefits as well as drawbacks, examples of drawbacks use a neural network. The nature of learning models necessitates in a training set multiple iterations. The majority of learning algorithms have system parameters that should be chosen manually by a user of an algorithm. As result, the system fails to be in depend and automated. The parameters of the system impact significantly the performance of each model. There is little or no instruction on how to choose the parameter that can influence the output quality. The algorithms' proclivity to encounter problems that needed resetting parameters is also a flaw in some algorithms[39].

2. 6. 2 .Unsupervised Learning

Unsupervised learning, artificial neural network don't need external elements to modify weights of the connection link between its neurons, don't get information that indicates the predicated outputs in response for decided inputs is right or not, which is why It's called unsupervised, also known the self-supervise[39].

2. 7 Machine Learning

Machine learning is a subset of artificial intelligence that is concerned with the design and development of techniques and algorithms that enable a computer to have the features that cause the computer to capable of learning without explicit programming. The main focus of machine learning is the computer program development that could be used to learn of an expansion well and to alter while it is subjected to new data [40]. Machine learning is programming the computer that uses for the purpose of improving a performance according to the criteria through repurposing previous data or experience. Machine learning has been classified as supervised and unsupervised consequently, supervised learning can be used to know what is learned in the past on a new dataset. unsupervised learning can derive conclusions from the data set[41].

2. 7. 1 Support Vector Regression

SVR algorithm works in an entirely different manner than most of the regression algorithms [42]. Where the other regression algorithms try to minimize the sum of squared error, SVR is concerned with the error when the error is in a particular range. This regression method works similarly to SVM, but instead of providing a class as output, it produces a real number. SVR gives flexibility in case of error to minimize coefficients (epsilon-value) and optimizes them to improve performance. It is trained with symmetrical loss function to penalize low, and high miss estimates equally. The computation complexity of SVR is not dependent on the input shape's dimension. For nonlinear operations, it uses kernel functions like Gaussian RBF kernel, it possesses excellent generalization capability, which is represented by eq. (2. 2), where x_i , x_j are two different observations in the dataset, and γ is the spread of the kernel.

$$f(x_i , x_j) = e^{-\gamma \|x_i - x_j\|^2} \quad (2.\ 2)$$

2. 7. 2 Multi-layer FFNN

A layered structure in feed-forward neural networks. Each layer is made up of nodes that get their inputs from nodes in the previous layer and send their outputs to nodes in the next layer. Within the layer, there are no connections. inputs are routed to the first hidden layer. The input node is just for input do not do any processing. The weighted input, plus the bias, is used to activate the function of the hidden node. The hidden node's output is spread over the following layer of hidden layers until the last hidden layer, the outputs of which are routed into the output layer[43]. Figure (2. 1) shows the typical architecture of FFNN.

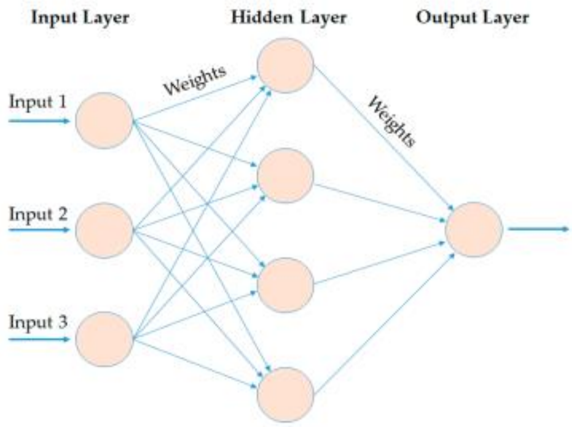


Figure (2. 1): Typical architecture of FFNN[43].

The optimal choice of training algorithm and network architecture are critical elements for successful the algorithm of FFNN. Feed Forward NN works as:

Activation yn_j of the hidden unit, j is computed at in eq.(2. 3):

$$yn_j = b_j + \sum_{i=1}^{M} x_i \cdot V_{ij} \qquad (2.3)$$

where the b represents bias weight, m represents the number of the inputs unit, x represents the inputs whose taken from a dataset, and v is the weight between an input layer and hidden layers.

value y of hidden unit j is computed at eq.(2. 4):

$$y_j = f(yn_j) \qquad (2.4)$$

Where $f(yn_j)$ is the result of applying the activation function at the hidden layer's unit j. Activation yn_j of the hidden unit, j is computed at eq.(2. 5):

$$zn_j = b_o + \sum_{j=1}^{N} y_j \cdot w_{jo} \qquad (2.5)$$

where the b represent bias weights, N represent the number of the hidden unit, y represent the hidden layer value, and w is a weight between hidden layers and output. value z of a output unit o is computed as in eq.(2. 6):

$$y_o = f(zn_j) \qquad (2.\ 6)$$

Where $f(zn_j)$ is the result of applying the activation function at the output layer's unit o. Squared error of output unit o is computed at eq.(2. 7):

$$e_o = \frac{1}{2}(y_o - t_o)^2 \qquad (2.7)$$

where t_o = actual values, y_o = prediction values and error propagated backward. According to error the weight updating as in eq.(2. 8)(2. 9):

$$V_{ij} = V_{ij}\,\eta\, y_j\,(y_j - 1)X\,(i)\sum_{o=1}^{M} w_{jo}\,.\,e_o \quad (2.8)$$

$$w_{jo} = w_{jo} + \eta\, y_j\, e_o \quad (2.9)$$

Where η = learning rate.

2. 8 Deep Learning

Deep learning (Deep Neural Network is another name for deep neural learning) constitutes a subset of machine learning in the field of AI, which has a network that is capable of learning the two types supervised and unsupervised learning. Deep learning is a type of AI function that mimics the operation of the human brain's processing of data and creation of patterns for use in the decision-making process[44], don't a single definition for deep learning, However, the majority of definitions sure following aspects:

- a subset of ML.
- Models are usually nonlinear.
- Uses the algorithms of supervised and unsupervised learning to fit models with the dataset.
- Model is graph structures, with many layers (deep).

2. 8. 1 Recurrent Neural Network

The recurrent neural net was developed for the first time in the 1980s[45-46]. Its structure is made up of the input layer, the output layer, and one or several hidden layers. RNNs are built from chain-like of modules that are repeated to employ these modules as the memory for storing important information of the prior processing stages. In contrast to the feed-forward neural network, RNNs have a feedback loop that enables neural networks for accepting a series of inputs, as shown in figure (2. 2). This indicates that the result of step t-1 is sent back to a network to impact the step's result and for all succeeding steps. Therefore, RNN has demonstrated success in the learning sequences, as shown in figure (2. 3) processing sequential in a recurrent neural network.

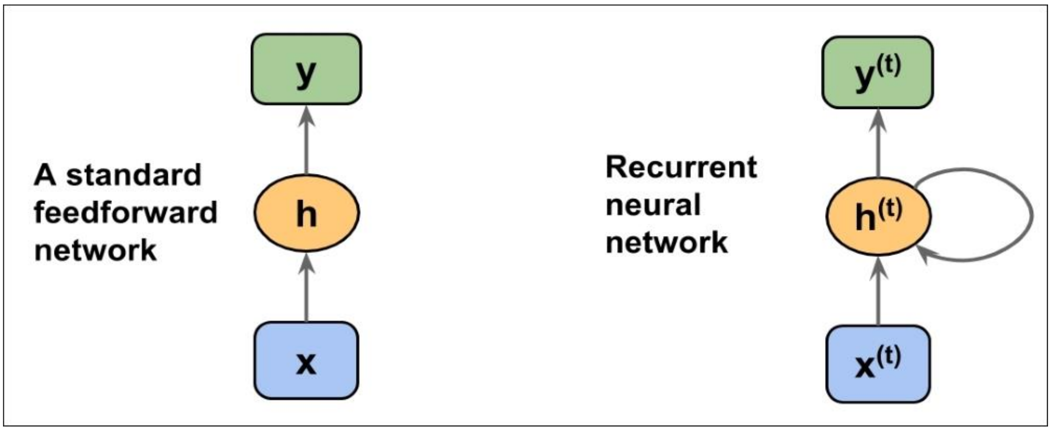


Figure (2. 2) : Difference between the FFNN and RNN

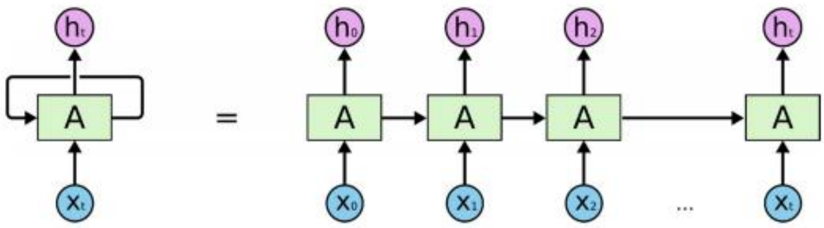


Figure (2. 3): The processing sequential in recurrent neural network[51].

Figure (2. 3) depicts a simple RNN, having one input node and single recurrent hidden layer expanding to the full network, and one output node, where x_t represents the input of the time step t, h_t represents the output of the time step t. RNN uses the back propagation method in the training process, a common method used in ANN for computing gradients and updating the weights. However, the weights will be adjusted and updated, as a result of the feedback process's adjustment. Therefore, its commonly referred to as back propagation through time. A BPTT process employs a backward technique, layer after layer, of the ultimate output of the network, adjusting the weights of each node based on its calculation from the overall outputs error. Information loops keep repeating, leading to massive updates of model weights and an unstable model owing to the buildup of the error gradients throughout the process of updating. As a result of an exploding gradient and gradient vanishing issues[47], BPTT is ineffective sufficiently for learning a pattern of the long-term dependency[48], this is one of the major causes for problems in training RNN[49].

2. 8. 2 Long Short-Term Memory Neural Network

Long short-term memory development of the recurrent neural network, was first presented by "Hochreiter and Schmidhuber"[50], to solve the issues raised by the RNN's aforementioned shortcomings, by incorporating extra interactions with each module. LSTM is a type of RNN, able to learn long-term dependency and remember information for a long time[51]. LSTMs models are arranged in a form structure of the chain. However, the structure of the repeating module is different. Instead of one neural net, like in a recurrent neural network, it comprises four interconnected levels and a distinct communication mechanism. Figure (2. 4) shows the architecture of the LSTM neural network.

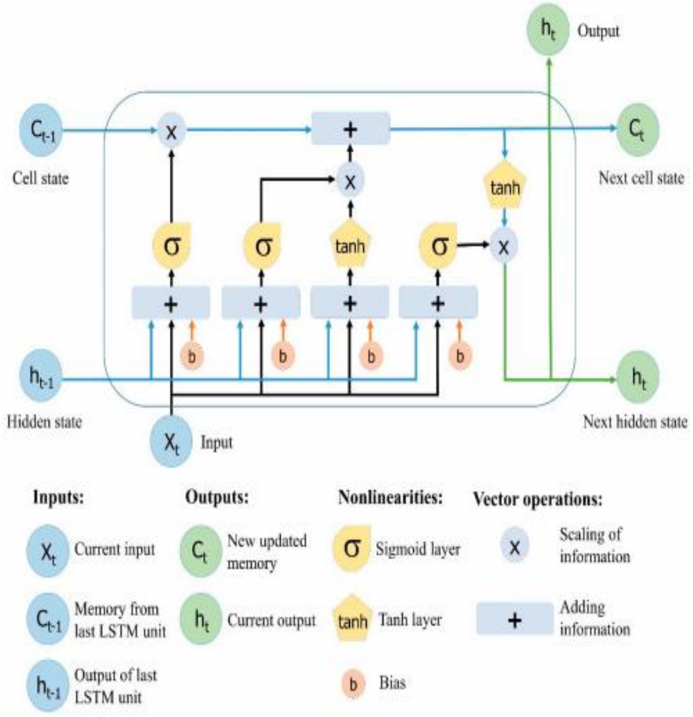


Figure (2. 4): The architecture of LSTM neural network[52].

The LSTM network is made up of memory blocks known as cells. Two situations are being transmitted for the next cell, hidden state, and cell state. The main chain for the data flowing is a cell state, that permits data for flowing forward unaltered.

However, may occur certain linear transformations. Sigmoid gates allow data to be added or deleted of cell state, the gate is analogous to layer or the series from operations of a matrix, that contain individual different weights. LSTM is intended for avoiding long-term dependence problems, due to its controlling of the process of memorizing using gates.

The initial stage in building the LSTM net is to define the information which isn't necessary for this step and will be removed; the sigmoid function is responsible for identifying and excluding information, that takes the previous LSTM unit's output

at (h_{t-1}) time t – 1, and current inputs (x_t) of the time t. Furthermore, the sigmoid function define whether parts of the previous output ought to be removed, this gate is known as forget gate (F_t), where (F_t) the vector whose values range the 0 to 1, corresponding for all a numbers of a cell state (C_{t-1}), represented by Eq.(2. 10).

$$F_t = \sigma\,(w_F\,[\,h_{t-1}\,,x_t\,]\,+b_F) \qquad (2.\ 10)$$

Where, (σ) is the sigmoid function, b_F and w_F are a bias and weight matrix of forget gate.

The next step is to decide and save data of new inputs (x_t) at cell state and for up to date a cell state, consist of two portions, sigmoid layer, followed by tanh layer, sigmoid decide whether to update or ignore new information (0 or 1), tanh function assigns weight for values that are passed to it, determining their importance (-1 to 1) and update a cell state by multiplied the two value. the new memory combined with the existing memory C_{t-1} for result C_t.

where, C_{t-1} and C_t. Are cell state of the time t − 1 and t, b and W are the bias and weight matrix, as in the following equations.

$$I_t = \sigma\,(w_I\,[\,h_{t-1}\,,x_t\,]\,+b_I) \qquad (2.\ 11)$$

$$n_t = \tanh\,(w_n\,[\,h_{t-1}\,,x_t\,]\,+b_n) \qquad (2.\ 12)$$

$$C_t = C_{t-1}F_t + n_tI_t \qquad (2.\ 13)$$

in the last step, output values (h_t) are based on cell state (O_t). At first, the sigmoid determines which elements of the cell state are output. Following, sigmoid gate output (O_t), is then multiplied by the new value of (tanh) cell state (C_t) as in the following equations.

$$o_t = \sigma\,(w_O\,[\,h_{t-1}\,,x_t\,]\; + b_O) \quad (2.\ 14)$$

$$h_t = o_t \tanh\,(C_t) \qquad (2.\ 15)$$

Where b and W are the bias and weight matrix, of the output gate.

CHAPTER THREE

Research Methodology

CHAPTER THREE

3. 1 Introduction

This chapter introduces the Methodology of work and describes the phases of building the proposed system for earthquake prediction, focuses on the use and comparison of machine learning techniques. Support vector regression, feed forward neural network and long short term memory algorithm will be used, their performance will be evaluated based on metrics such as accuracy and MSE. These techniques will be applied to the dataset of Iraq which is used to train and test the models. The experience is carried out on two variables, four variables and five variables, and the results are evaluating using the evaluation criteria, preprocessing will be performed by remove duplicate from the used dataset and normalization, dataset will be splitted into two groups; a training dataset for train the models and a testing dataset for testing the models.

3. 2 The Proposed System (Earthquake Prediction)

The schematic representation of the proposed system is shown in figure (3.1).Firstly, collection the data that used, to predict the earthquake time, location, depth, and magnitude of the next occurrence based on the historical data of the earthquakes. After that, applying the preprocessing approach on these dataset, this approach contain remove duplicate from the used dataset and normalization that defined as cleaning dataset.

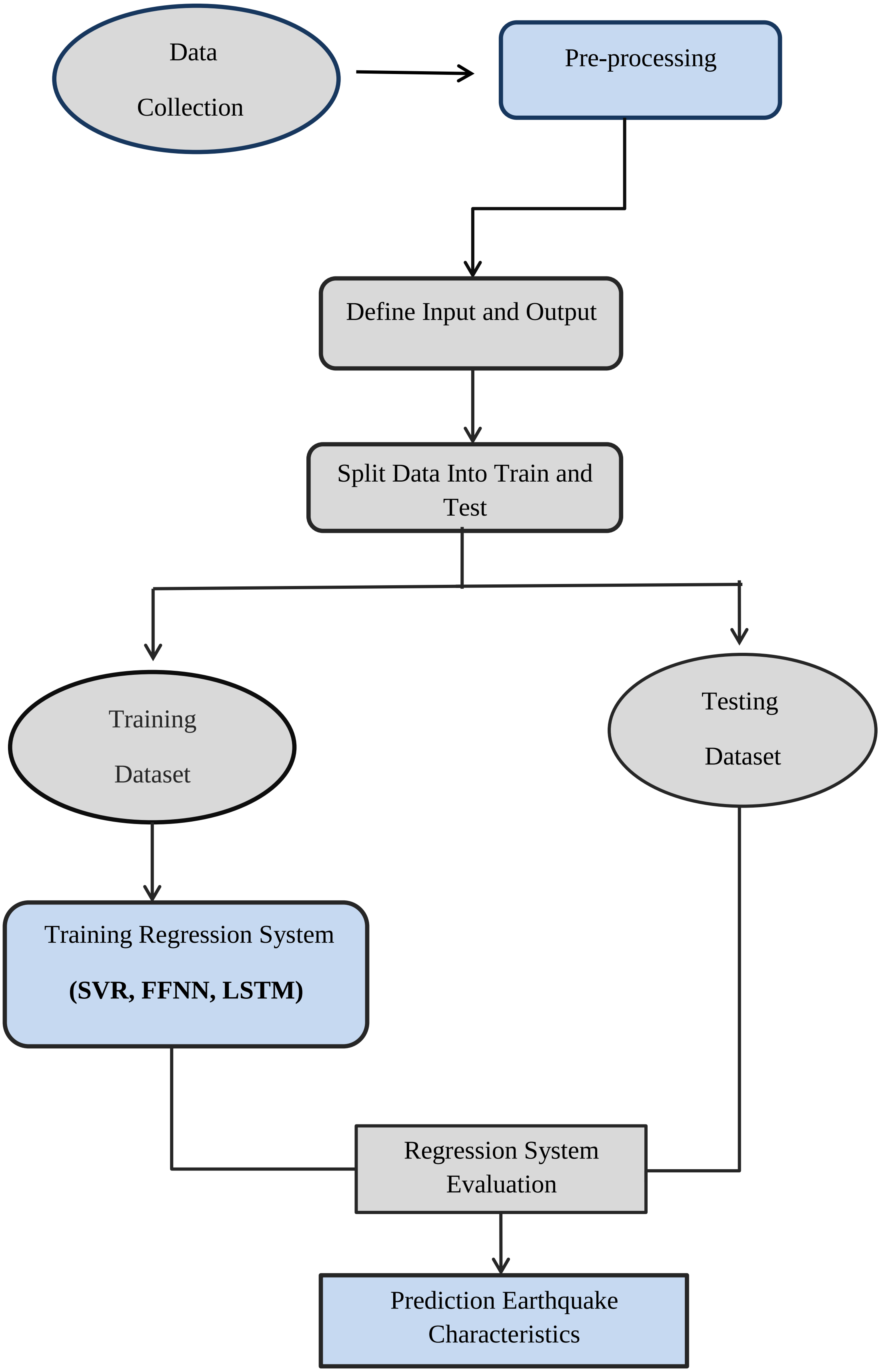


Figure (3. 1): Block diagram of the prediction model

This work attempt to forecast the earthquake time, location, depth, and magnitude of the next occurrence based on the historical data of the earthquakes. When an earthquake occurs, the recorded information about it is used to predict the next events, using the algorithm of feed-forward nets and Long short-term memory.
The inputs to the proposed system are the number of characteristics to be utilized for prediction. Outputs are equal to the number of input characteristics because the predicted information of the next event is based on data from past events. The input data and the target data are described in figure (3. 2).

Target Data

Time	x_1^1	x_1^2	x_1^3	$\cdots$	x_1^{N-1}	x_1^N
Latitude	x_2^1	x_2^2	x_2^3	$\cdots$	x_2^{N-1}	x_2^N
Longitude	x_3^1	x_3^2	x_3^3	$\cdots$	x_3^{N-1}	x_3^N
Depth	x_4^1	x_4^2	x_4^3	$\cdots$	x_4^{N-1}	x_4^N
Magnitude	x_5^1	x_5^2	x_5^3	$\cdots$	x_5^{N-1}	x_5^N

Input Data

Figure (3. 2): The input and target data in proposed system

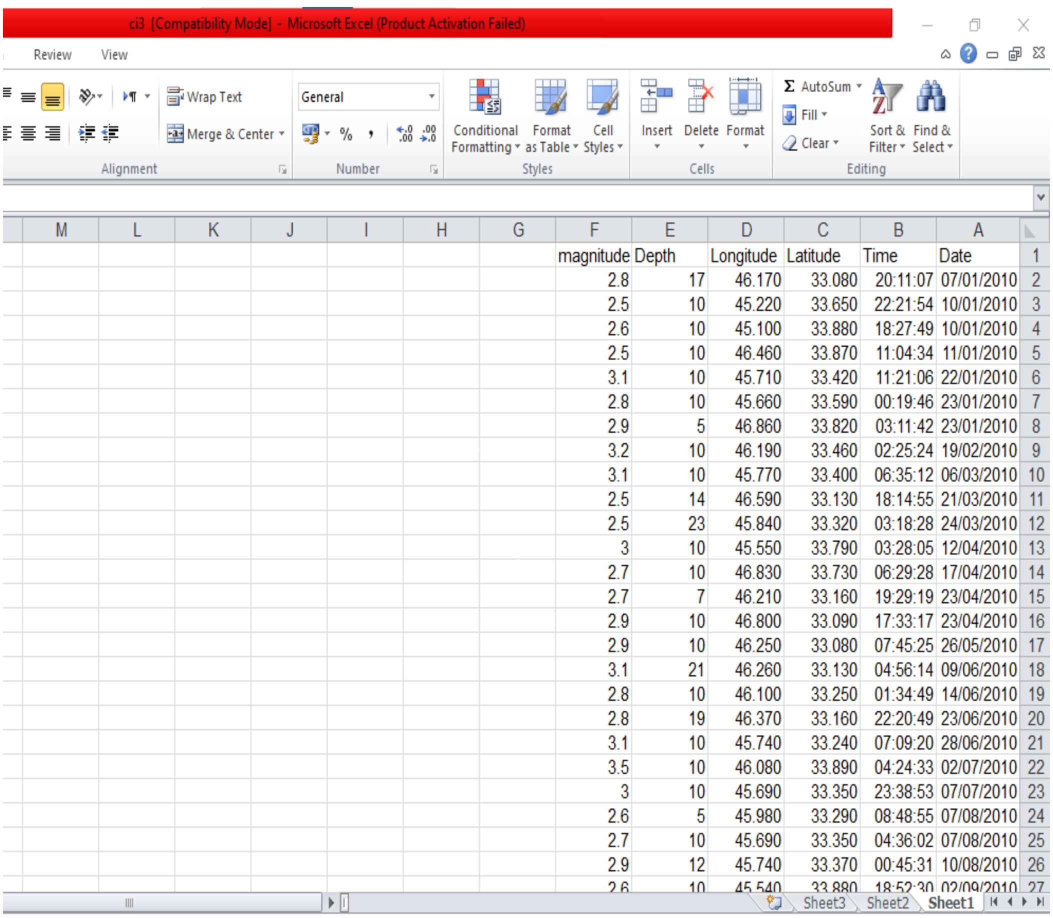
Where x_1, x_2, x_3, x_4, x_5,represent the earthquake characteristics (Time, Latitude, Longitude, Depth, Magnitude) and N represent the number of samples.

3. 3 Dataset

The dataset for this study was obtained from the General Directorate of Meteorology and Seismic Monitoring in Iraq, as it is real data recorded by this directorate and facilitates work to obtain good forecasts, this dataset contains the variables (time, date, longitude, latitude, depth and earthquake magnitude) collection from Jan 2010 to act 2020. For three region of Iraq (Sulaymaniyah, Wasit and Maysan). Dataset description:

- Date: the date on which it occurred (year/month/day).
- Time: occur at a specific moment (hours/minutes/second).
- Latitude and Longitude: Location tracking (according to the coordinates of the place).
- Depth: the location of the epicenter (measured in kilometers).
- Magnitude: earthquake magnitude (measured on the Richter scale).

The figure (3. 3) Shows the content of the dataset.



magnitude	Depth	Longitude	Latitude	Time	Date	1
2.8	17	46.170	33.080	20:11:07	07/01/2010	2
2.5	10	45.220	33.650	22:21:54	10/01/2010	3
2.6	10	45.100	33.880	18:27:49	10/01/2010	4
2.5	10	46.460	33.870	11:04:34	11/01/2010	5
3.1	10	45.710	33.420	11:21:06	22/01/2010	6
2.8	10	45.660	33.590	00:19:46	23/01/2010	7
2.9	5	46.860	33.820	03:11:42	23/01/2010	8
3.2	10	46.190	33.460	02:25:24	19/02/2010	9
3.1	10	45.770	33.400	06:35:12	06/03/2010	10
2.5	14	46.590	33.130	18:14:55	21/03/2010	11
2.5	23	45.840	33.320	03:18:28	24/03/2010	12
3	10	45.550	33.790	03:28:05	12/04/2010	13
2.7	10	46.830	33.730	06:29:28	17/04/2010	14
2.7	7	46.210	33.160	19:29:19	23/04/2010	15
2.9	10	46.800	33.090	17:33:17	23/04/2010	16
2.9	10	46.250	33.080	07:45:25	26/05/2010	17
3.1	21	46.260	33.130	04:56:14	09/06/2010	18
2.8	10	46.100	33.250	01:34:49	14/06/2010	19
2.8	19	46.370	33.160	22:20:49	23/06/2010	20
3.1	10	45.740	33.240	07:09:20	28/06/2010	21
3.5	10	46.080	33.890	04:24:33	02/07/2010	22
3	10	45.690	33.350	23:38:53	07/07/2010	23
2.6	5	45.980	33.290	08:48:55	07/08/2010	24
2.7	10	45.690	33.350	04:36:02	07/08/2010	25
2.9	12	45.740	33.370	00:45:31	10/08/2010	26
2.6	10	45.540	33.880	18:52:30	02/09/2010	27

Figure 3. 3: Dataset of earthquakes

3. 4 Dataset Preprocessing

Before applying learning algorithms to the dataset, it's critical to carry out data normalization and pruning, data reduction is the process of merging one or more characteristics that represent the same characteristics of any object where that contribution to the training algorithm is considered only once. Additionally, some characteristics may appear superfluous and thus be deleted from the dataset. This is sometimes called data cleansing, it improves the training performance and the algorithm's efficiency. Following, these steps an algorithm is learned to anticipate the target result. Before utilizing the dataset for a prediction, at this stage, the two characteristics of (time and date) merged into a single column. They help to forecast earthquakes by contributing to the time date and sorting the data according to the time, the variables have different ranges of values as seen in figure (3. 4). It is not good for model training. So, the normalization is carried out for the data .The mean of a signal is:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x\ (i) \qquad (3.\ 1)$$

The standard deviation of the signal is:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\mu)^2} \qquad (3.\ 2)$$

Normalization is the process of scaling values such that they lie in a narrowly defined domain. It is beneficial for enhancing the learning process.

of the signal is:

$$x'(i) = \frac{x\ (i)\ -\mu}{\sigma}, \quad i = 1, \ldots, N. \qquad (3.\ 3)$$

(x') The normalized data, $x\ (i)$ the original data,. μ is the mean deviation, σ is a standard deviation.

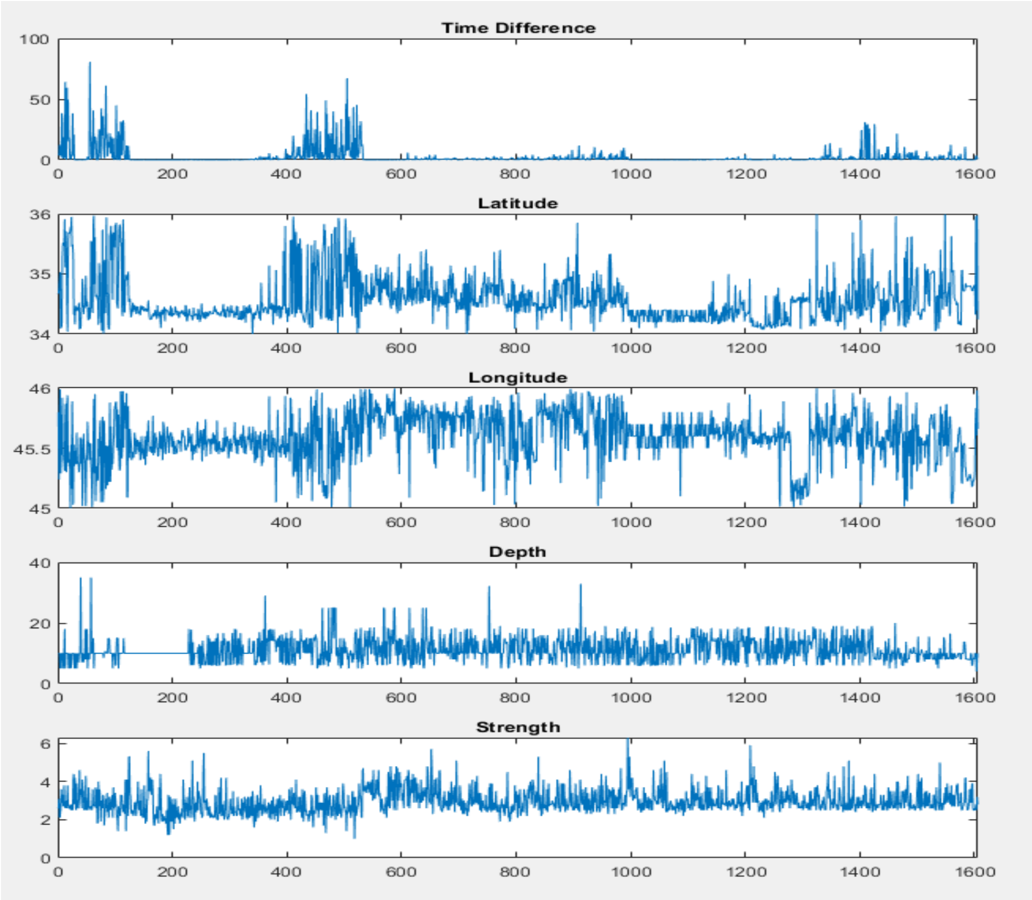


Figure 3. 4: Value of variables

Where the x-axis represents the number of samples for earthquake characteristics and the y-axis represents the range of the dataset.

3. 5 Support Vector Regression Algorithm

SVR method differs from other regression algorithms in that it operates in a completely different way. Whereas other regression methods aim to reduce the sum of squared error, SVR is more concerned with the error when it falls inside a certain range. For predict earthquake characteristics, in SVR model the most important parameter and used depending on datasets it kernel function. Radial basis function is used and the coefficient Epsilon-values set to (0.1). Figure(3. 5),show the flowchart of SVR.

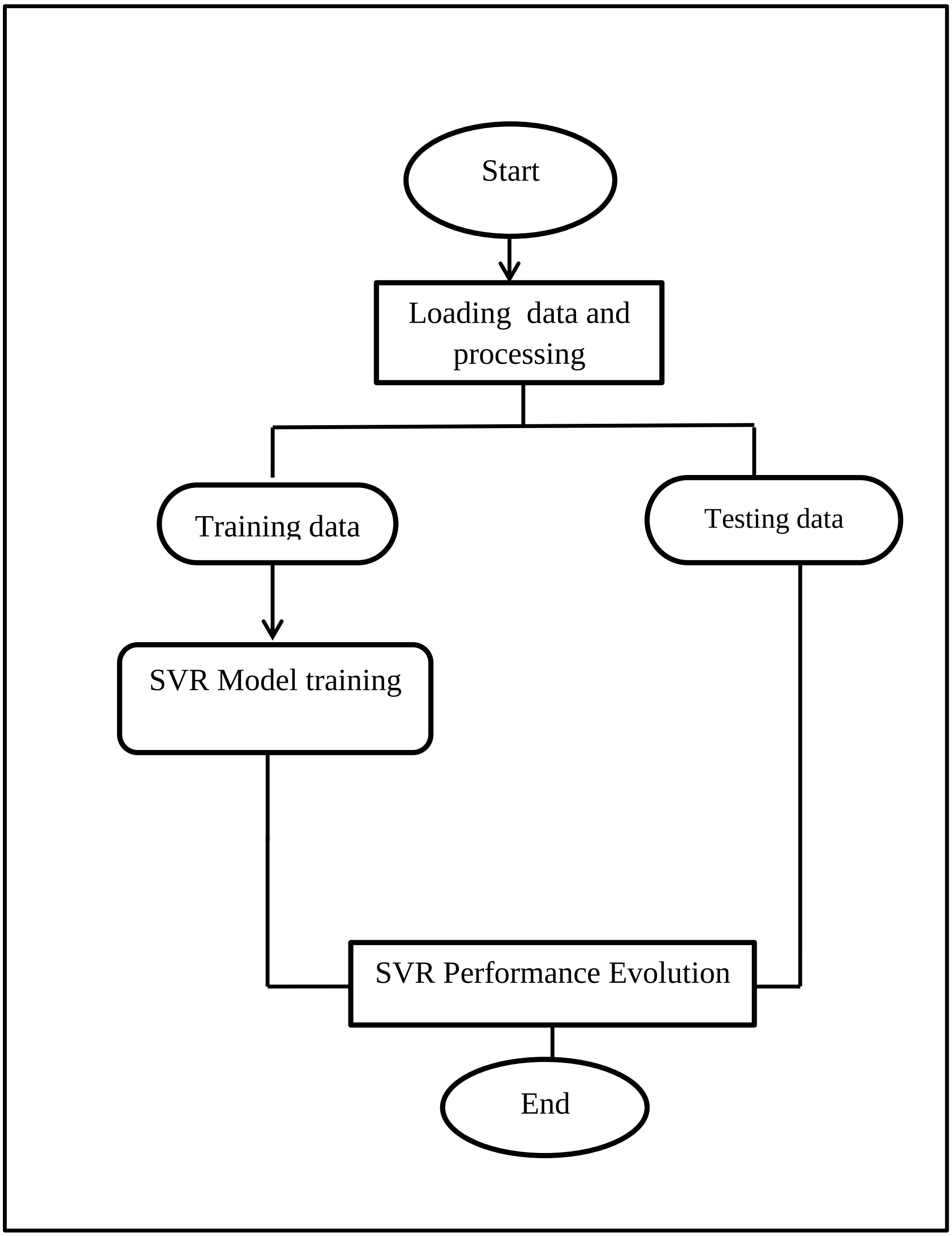


Figure (3. 5): Flowchart of the proposed support vector regression

3. 6 Feed Forward Neural Network Algorithm

Feed-forward networks are not cyclic networks that are often organized in layers, with each neuron receiving input solely from the one immediately before it. The FFNN algorithm has three layers: the input, hidden, and output layers. The neural network is trained using an algorithm of the gradient descent optimization and weights are adjusted using the back propagation technique, based on errors as computed by the loss function. In the majority of neural networks, the loss function is used to compute the difference between expected output and actual output, for a variety of issues, including regression. The BP training technique is a supervised learning approach that optimizes the network to reduce the loss function by updating the weights of neural networks. Backward propagation of the current mistake to a previous layer by computing the loss function's gradients.

The model has two hidden layers, each with 20 and 35 nodes. The sigmoid function is used to activate all nodes. The gradient descent was utilized as the learning rule. The dataset is used to train this model for 500 epochs, with a learning rate of 0. 01. These characteristics were chosen using a grid search that determined the optimum design based on the error. Figure (3. 6). shows the flowchart of the FFNN.

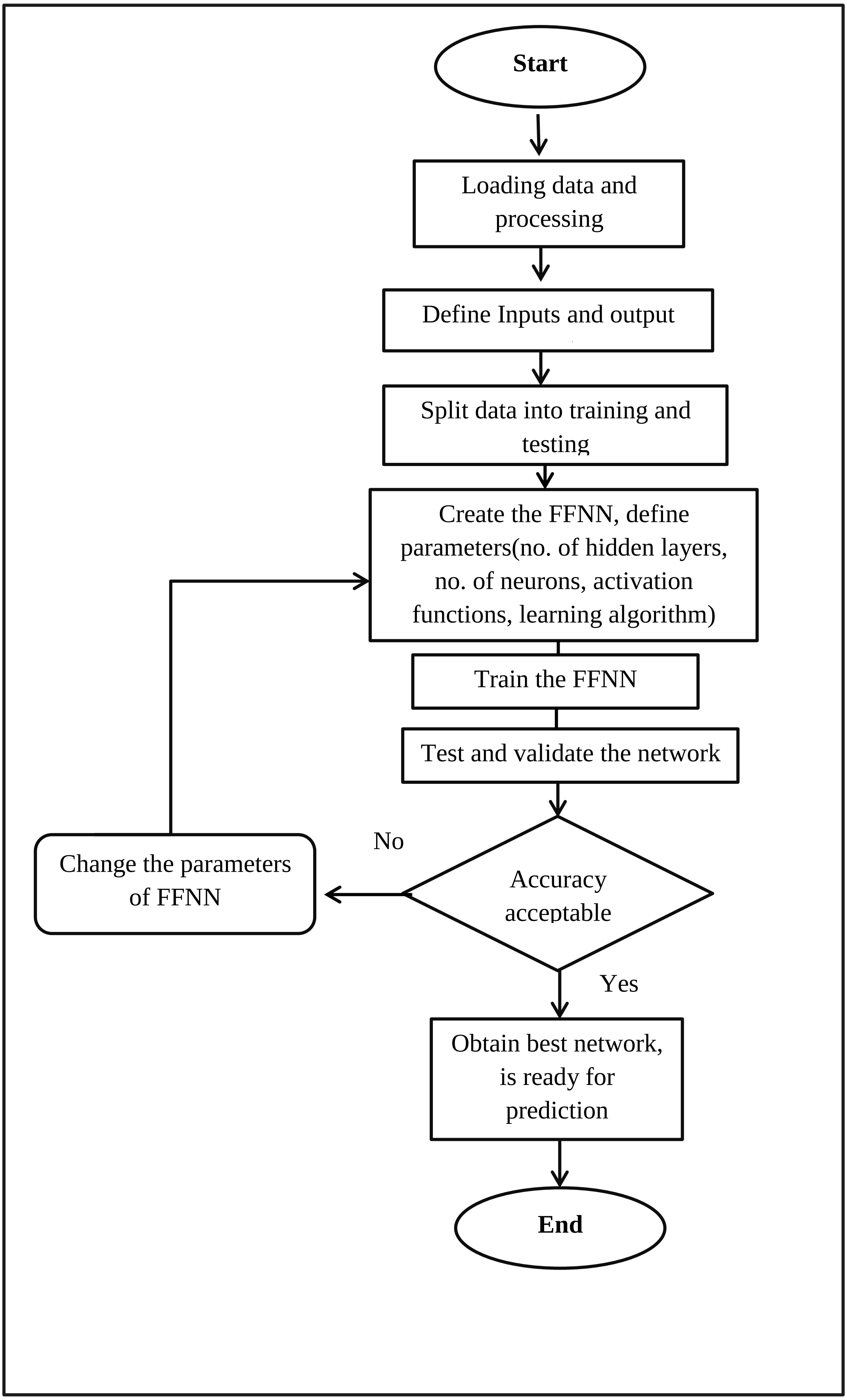


Figure (3. 6): Flowchart of the proposed feed-forward neural network

Algorithms 3. 1: Pseudo Code of FFNN

Inputs: Earthquake characteristics
Output: Earthquake characteristics
Initialization
Set number of Hedin layers, NumOfHlyr=2;
FirstHlyr_nodes= 20;
SoundHlyr_nodes = 35;
Set number of iterations, NumOfIter=500;
x: Input data ;
t: Output data;
n: number of sample;
W: weight matrix ;
b: bias
η: learning rate;
L: number of hidden layers;
N: number of neurons per layer;
ITmax: number of iteration;

Processing
X: normalization (x)
ITmax=1;
While (ITmax < = *NumOfIter*)
compute the output y for each training vector (x, t) :
for **i=1**: **n**

$$y = f\sum_{i=1}^{n} xi.wi + b$$

Calculate error:

$$e_o = \frac{1}{2}(y_o - t_o)^2$$

for **j= 1:n**
Update weight vector V_{ij}:

$$V_{ij} = V_{ij}\,\eta\, y_j\,(y_j - 1) X\,(i) \sum_{o=1}^{M} U_{jo}\,.\,e_o$$

$$U_{jo} = U_{jo} + \eta\, y_j\, e_o$$

M++;
j++;
i++;
ITmax **++;**
End for
End for
IF Accuracy not met
Update L, N, ITmax, η;
End if
End while

3. 7 LSTM Neural Network Algorithm

A long short- term memory network is a type of RNN. In sequential data regression uses the LSTM neural network for predicting the earthquake of the next occurrence, the proposed LSTM model has two hidden layers, each with 200 hidden units of LSTM cells. For regularization, two dropout layers are added among the LSTM layers. To avoid overfitting, will randomly prohibit (0. 2) of the preceding layer's activations from propagating. The RMSprop [53] algorithm is used to reduce the mean square errors, It increases learn rate of the sporadic parameters while decreasing learn rate of the sporadic ones in situations when data is scarce, this method frequently outperforms traditional gradient descent in terms of convergence. Learn rate is set at 0.01, the number of iterations reached 500, the dataset is split into the training data and testing data. The ratio between the training data and testing data is set as 7:3. After experimenting with several architectures, these parameters are chosen as the best parameters. The architecture of the proposed LSTM neural network has several layers. LSTM layer is the first layer through which an input matrix is sent from sequence layer. Then, the output of the LSTM layer is subjected to a dropout process, overfitting is a significant issue in deep neural net with many parameters, make difficult to cope with overfitting. Dropout is a method of dealing with this problem, the key concept is to randomly remove units (in addition to their connections) during the training of the neural network. This keeps units from over-co-adapting. Dropout enhances neural networks performance in supervised learning [54]. Results of the dropout layer go to the Relu layer[55], and the fully connected layer. Finally, the output regression layer as shown in figure (3. 7).

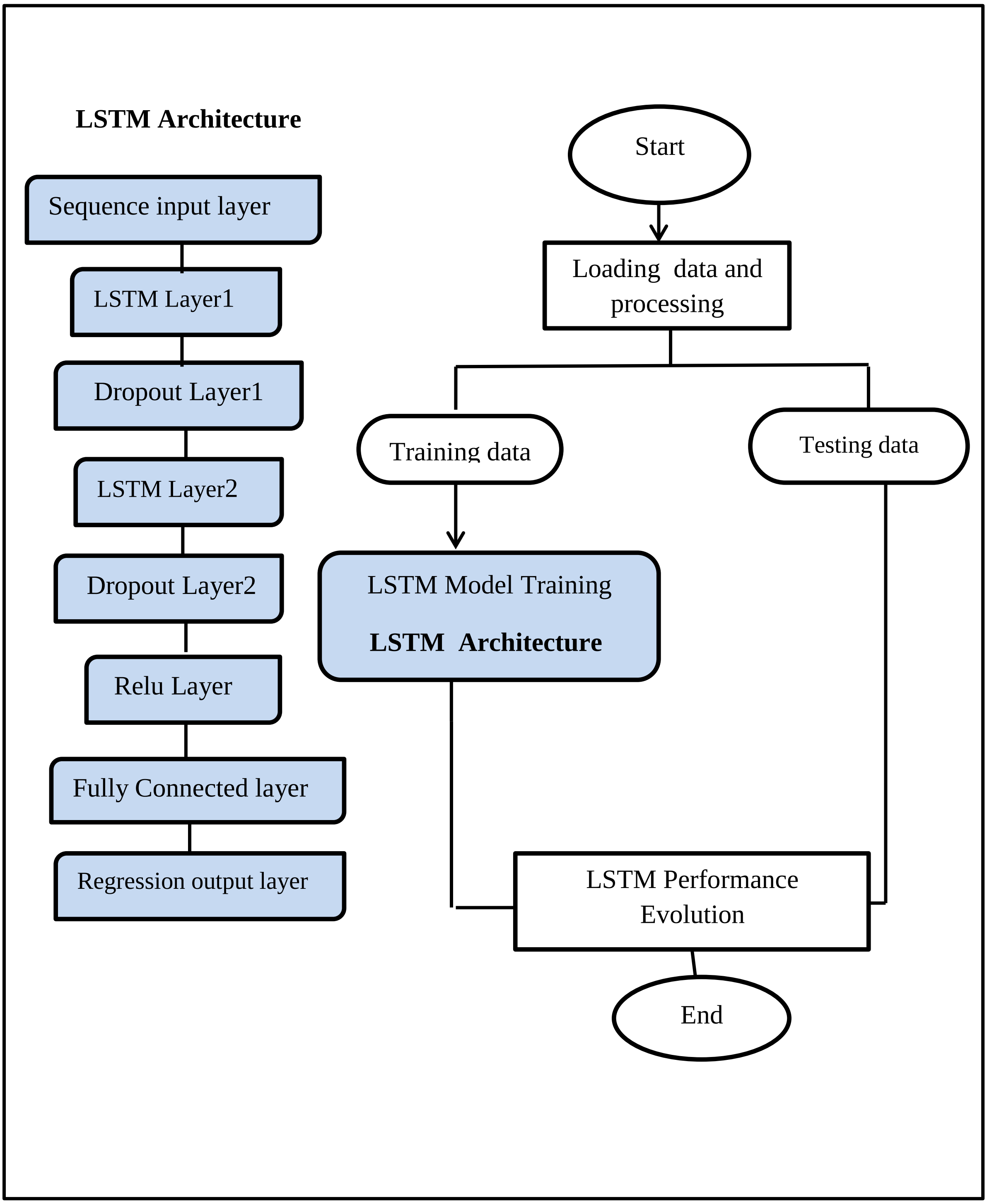


Figure (3. 7): Flowchart of the proposed LSTM neural network

Algorithms 3. 2: Pseudo Code of LSTM

Input: Earthquake characteristics
Output: Earthquake characteristics
Initialization
Initialize LSTM network parameter: (hidden layer, hidden layer nodes, learning rate, batch_size, optimizer) ;
Set number of iterations, NumOfIter=500;
Set number of Hedin layers, NumOfHlyr=2;
FirstHlyr_nodes= 200;
SoundHlyr_nodes = 200;
learning rate =0. 01;
batch_size =128;
optimizer = RMsprop ;
x: input data;
t= output data
maxIT: max itration;
Implementation
maxIT***=1;***
while (maxIT < = *NumOfIter*) do
Calculate LSTM output: $\boldsymbol{h_t = o_{t\,0}}\emptyset\ (\boldsymbol{C_t})$; base eq. (2. 15)
Dropout layer probability (0. 2%) ;
Applied Relu activation function on the output: $\boldsymbol{f(x) = \max(0, x)}$
fully-connected layer according to: $\boldsymbol{h_t^D}=\boldsymbol{v_D\ h_t^L + b}$l;
Calculate the loss function: Loss = $\boldsymbol{\frac{1}{n}\sum_i^n (y_i - t_i)^2}$; base eq. (3. 7)
maxIT++**;**
End while

3. 8 Proposed of Evaluation Criteria

When a model is constructed, the next crucial step is to evaluate its performance, to assess the performance of predicting models. accuracy and MSE are statistical methods frequently utilized to compare between expected and actual results, accuracy measures the capacity to predict different variables. MSE is often used to assess how closely expected values match actual values. according to the data's relative range. The accuracy of the model calculating using testing data for resulting system data, the standard deviation is computed to determine the correct samples, as shown in table (3. 1).

Table 3. 1: Standard deviation of variables

$Dataset$	Variables (Earthquake Characteristics)				
	Time	Latitude	Longitude	Magnitude	Depth
standard deviation of Sulaymaniyah Dataset	4320	0.245	0.311	0.3	3.5
standard deviation of Maysan Dataset	6850	0.260	0.492	0.3	4.15
standard deviation of Wasit Dataset	7473	0.277	0.326	0.3	4.6

Where the correct prediction can be calculated by the difference between the actual values and predicted values smaller than the standard deviation of the variable.

Correct prediction=$|actual\ value - predicted\ value| < standard\ deviation\ of variable.$

The accuracy of Time and Magnitude is measured as:

$$\text{Acc.} = \frac{\mathbf{DtMg + Dt + Mg}}{\mathbf{DtMg + Dt + Mg + I}} \times 100 \qquad (3.4)$$

Where:

- **DtMg** represents the number of forecasts that were right both in terms of timing and magnitude.
- **Dt** represents the number of forecasts that were right in terms of time but wrong in terms of magnitude.
- **Mg** represents the number of forecasts that were incorrect in terms of time but correct in terms of magnitude only.
- **I** is the number of times a prediction has been wrong in terms of magnitude and time.

Accuracy of Time, Magnitude, Location is measured as:

$$\text{Acc.} = \frac{S\,3 + S\,4}{N} \times 100 \qquad (3.5)$$

$N = S1 + S2 + S\,3 + S\,4 + I.$

Where

$N = total\ numbers\ of\ test\ samples.$

$S\ 1 = one\ variable\ is\ correct.$

$S\ 2 = \ Two\ variable\ are\ correct.$

$S\ 3\ = Three\ variables\ are\ correct$

$S4\ = Four\ variables\ are\ correct.$

I= All variables are incorrect.

Accuracy of Time, Magnitude, Location, Depth is measured as:

$$\text{Acc.} = \frac{S\ 3 + S\ 4 + S5}{N} \times 100 \qquad (3.6)$$

$N = \ S1 + S2 + S\ 3 + S\ 4 + S5 + I$

Where

$N = total\ numbers\ of\ test\ samples.$

$S\ 1 = One\ variable\ is\ correct.$

$S\ 2 = \ Two\ variable\ are\ correct.$

$S\ 3\ = Three\ variables\ are\ correct.$

$S4\ = Four\ variables\ are\ correct.$

$S\ 5\ = Five\ variables\ are\ correct.$

I= All variables are incorrect.

The mean squared error (MSE)

$$\text{MSE} = \frac{1}{N}\sum_{i}^{N}(y_i - t_i)^2 \qquad (3.7)$$

Where y_i represents the predicted value, t is the actual value, and N is the number of testing samples.

CHAPTER FOUR

Results and Discussion

CHAPTER FOUR

4. 1 Introduction

This chapter presents the proposed system's implementation and evaluation of an earthquake prediction based on historical data. Earthquakes are natural calamities generated by a movement of the earth's tectonic plates as a consequence of its release of internal energy, more powerful earthquake might lead to huge loss of life and major infrastructure damage. the earthquake can be expected, the damage may be minimized, full earthquake the forecast procedure must contain three of earthquake information: the location, magnitude and the time of its event. Artificial intelligence techniques have been used in different aspects such as financial forecasting, water resources engineering, image processing, because have the ability to uncover patterns of hidden and nonlinear relationships in data, in this thesis use techniques of AI in earthquake prediction. prediction performance of the proposed system (earthquake prediction system) is evaluated by testing it with testing data applied on two variables, four variables, five variables, for three regions by using a variety of metrics such as Accuracy and MSE.

Software and tools; this work was implemented using a PC have Microsoft Windows 10 (Ultimate 64-bit), with a processor an Intel Core i5 processor, 1. 90GHz 2.50 GHz with 8GB of RAM. MATLAB (R2020b) was utilized to implement the system, it is efficient, fast enough, and takes a short time to implement the proposed algorithms.

4. 2 Earthquake prediction using SVR

Earthquake datasets of three regions of Iraq were selected for training and testing the proposed system of earthquake prediction

1**-The first region is Sulaymaniyah**. The city of Sulaymaniyah is located between latitudes (34-36) degrees and longitude (45-46) degrees of the globe and occur in them several earthquakes of different strength, between weak and medium ones. The recorded earthquakes range in strength from (2. 5 to 5. 5) and their depth reaches (18. 3) km. Events from 2010 to 2020.

❖ **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude. the number of recorded earthquake events, the number of events (942) selected for training, and the number of events (403) selected for testing. Table (4. 1) shows the result of predicting the earthquake's time and magnitude for the Sulaymaniyah region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 118sample. **Dt** represents the event where the predict of time only is True and it was 63 sample. **Mg** represents the event where the predict of magnitude only is True and it was 101 sample. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 121 sample and the accuracy is 69%.

❖ **Predicting the earthquake's time, magnitude, and location:**

Table (4. 2) shows the result of predicting earthquake's time, magnitude, and location for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 36 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 45 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 155 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 135 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was 32 samples and the accuracy is 71%.

❖ **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 3) shows the result of predicting earthquake's time, magnitude, location, and depth for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 44 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 47 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 118 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 82 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 92 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 20 samples and the accuracy is 72%.

Table 4. 1: Describe dataset of predict the earthquake's time and magnitude in Sulaymaniyah using SVR.

Items	values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of **DtMg**	118
No. of **Dt**	63
No. of **Mg**	101
No. **I**	121
Accuracy	0.69

Table 4. 2: Describe dataset of predict the earthquake's time, magnitude and location in Sulaymaniyah using SVR.

Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	36
No. of Two variable correct **S2**	45
No. of three variables correct **S3**	155
No. of four variables correct **S4**	135
No. of all variable incorrect **I**	32
Accuracy	0. 71

Table 4. 3: Describe dataset of predict the earthquake's time, magnitude, location and depth in Sulaymaniyah using SVR.

Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	44
No. of Two variables correct **S2**	47
No. of three variables correct **S3**	118
No. of four variables correct **S4**	82
No. of five variables correct **S5**	92
No. of all variables incorrect **I**	20
Accuracy	0. 72

2- **The second region is Maysan**, The city of Maysan is located between latitude (31-32) degrees and longitude (46-47) degrees of the globe and occur in them several earthquakes of different strength, between weak and medium ones. The recorded earthquakes range in magnitude from (2. 5 to 6), and their depth reaches (17. 5) km. Events from 2010 to 2020.

- **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude, the number of recorded earthquake events, number of events (882) selected for training, and number of events (376) selected for testing. Table (4. 4) shows the result of predicting earthquake's time and magnitude for the Maysan region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 132 sample. **Dt** represents the event where the predict of time only is True and it was 45 sample. **Mg** represents the event where the predict of magnitude only is True and it was 88 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 111 sample and the accuracy is 70%.

- **Predicting the earthquake's time, magnitude, and location:**

Table (4. 5) shows the result of predicting earthquake's time, magnitude and location for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 16 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 62 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 158 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 114 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was 26 sample and the accuracy is 72%.

- **Predicting the earthquake's time, magnitude, location and depth**

Table (4. 6) shows the result of predicting earthquake's time, magnitude, location, and depth for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 21 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 23 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 93 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 120 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 101 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 18 samples and the accuracy is 73%.

Table 4. 4: Describe dataset of predict the earthquake's time and magnitude in Maysan using SVR.

Items	Values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of **DtMg**	132
No. of **Dt**	88
No. of **Mg**	45
No. **I**	111
Accuracy	0. 70

Table 4. 5: Describe dataset of predict the earthquake's time, magnitude and location in Maysan using SVR.

Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	16
No. of Two variables correct **S2**	62
No. of three variables correct **S3**	114
No. of four variables correct **S4**	158
No. of all variables incorrect **I**	26
Accuracy	0. 72

Table 4. 6: Describe dataset of predict the earthquake's time, magnitude, location and depth in Maysan using SVR.

Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	21
No. of Two variables correct **S2**	23
No. of three variables correct **S3**	93
No. of four variables correct **S4**	120
No. of five variables correct **S5**	101
No. of all variables incorrect **I**	18
Accuracy	0. 73

3-**The third region is Wasit.** Wasit city located between latitude (32 -33) degrees and longitude (45-46) degrees of the globe and occur in them several earthquakes of different strength, between weak and medium ones. The recorded earthquakes range in strength from (2.5 to 5.5) and their depth reaches (18) km. Events from 2010 to 2020.

- **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude. the number of recorded earthquake events, the number of events (620) selected for training and the number of events (265) selected for testing. Table (4. 7) shows the result of predicting earthquake's time and magnitude for the Wasit region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 78 samples. **Dt** represents the event where the prediction of time only is true and it was 39 samples. **Mg** represents the event where the prediction of magnitude only is true and it was 45 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 103 sample and the accuracy is 61%.

- **Predicting the earthquake's time, magnitude and location:**

Table (4. 8) shows the result of predicting the earthquake's time, magnitude and location for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 27 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 24 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 99 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 78 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 37 samples and the accuracy is 63%.

❖ **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 9) shows the result of predicting earthquake's time, magnitude, location and depth for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 33 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 29 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 58 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 66 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 51 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 28 samples and the accuracy is 66%.

Table 4. 7: Describe dataset of predict the earthquake's time and magnitude in Wasit using SVR.

Items	Values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of **DtMg**	78
No. of **Dt**	39
No. of **Mg**	45
No. **I**	103
Accuracy	0. 61

Table 4. 8: Describe dataset of predict the earthquake's time, magnitude and location in Wasit using SVR.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	27
No. of Two variables correct **S2**	24
No. of three variables correct **S3**	99
No. of four variables correct **S4**	78
No. of all variables incorrect **I**	37
Accuracy	0. 63

Table 4. 9: Describe dataset of predict the earthquake's time, magnitude, location and depth in Wasit using SVR.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	33
No. of Two variables correct **S2**	29
No. of three variables correct **S3**	58
No. of four variables correct **S4**	66
No. of five variables correct **S5**	51
No. of all variables incorrect **I**	28
Accuracy	0. 66

4. 3 Earthquake prediction using FFNN

1- AL Sulaymaniyah Region

❖ **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude. the number of recorded earthquake events, the number of events (942) selected for training, and the number of events (403) selected for testing. Table (4. 10) shows the result of predicting the earthquake's time and magnitude for the Sulaymaniyah region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 200 sample. **Dt** represents the event where the predict of time only is True and it was 63 sample. **Mg** represents the event where the predict of magnitude only is True and it was 47 sample. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 93 sample and the accuracy is76%.

❖ **Predicting the earthquake's time, magnitude, and location:**

Table (4. 11) shows the result of predicting earthquake's time, magnitude, and location for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 26 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 50 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 195 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 120 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was12 samples and the accuracy is 78%.

❖ **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 12) shows the result of predicting earthquake's time, magnitude, location, and depth for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 23 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 43 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 112 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 127 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 91 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 7 samples and the accuracy is 81%.

Table 4. 10: Describe dataset of predict the earthquake's time and magnitude in Sulaymaniyah using FFNN.

Items	values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of **DtMg**	200
No. of **Dt**	63
No. of **Mg**	47
No. **I**	93
Accuracy	0.76

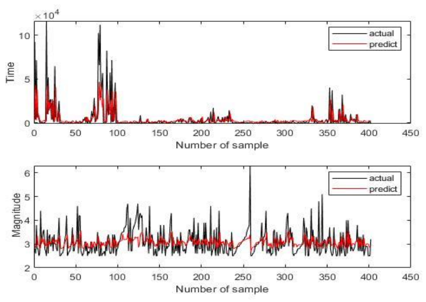
Table 4. 11: Describe dataset of predict the earthquake's time, magnitude and location in Sulaymaniyah using FFNN.

Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	26
No. of Two variable correct **S2**	50
No. of three variables correct **S3**	195
No. of four variables correct **S4**	120
No. of all variable incorrect **I**	12
Accuracy	0. 78

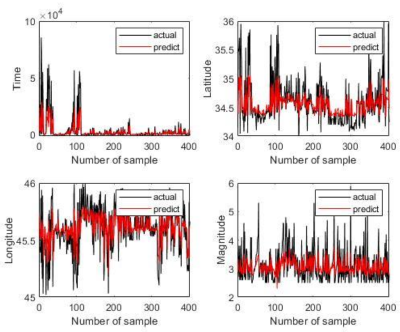
Table 4. 12: Describe dataset of predict the earthquake's time, magnitude, location and depth in Sulaymaniyah using FFNN.

Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	28
No. of Two variables correct **S2**	43
No. of three variables correct **S3**	112
No. of four variables correct **S4**	127
No. of five variables correct **S5**	91
No. of all variables incorrect **I**	7
Accuracy	0. 81

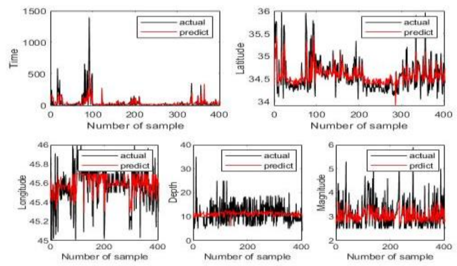
Figure (4:1) shows the actual values and predicted values of earthquake characteristics.



(a) time, magnitude



(b) time, magnitude, location



(c) time, magnitude location, depth

Figure 4:1 Prediction of earthquake characteristics for Sulaymaniyah using FFNN.

Figure (4:1) shows the prediction of earthquake characteristics, where 4:1 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Sulaymaniyah region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples, and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude, and earthquake location variables for the test data Sulaymaniyah region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth, and earthquake location variables for the test data Sulaymaniyah region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, the x-axis represents the number of test samples for the variables, and the y- axis represents the values of the variables.

The actual values and predicted values of earthquake characteristics, (time, magnitude, location, depth) for the Sulaymaniyah region testing dataset as shown in table (4. 13),these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations came with a slight difference from the real values.

Table 4. 13: Prediction of earthquake characteristics of Sulaymaniyah using FFNN

Time Actual	Time Predict	Magnitude Actual	Magnitude Predict
17822	17744	2. 9	3
30129	30129	3. 2	3. 2
47162	46832	2. 8	2. 8
74064	74062	4. 2	3. 9
63291	63316	3	3

Location Latitude		Location Longitude		Depth Actual	Depth predict
Actual	predict	Actual	Predict		
34. 595	34. 594	45. 788	45. 792	10	9. 8
34. 634	34. 632	45. 688	45. 693	11. 5	11. 4
34. 651	34. 649	45. 533	45. 533	12	12
34. 511	34. 514	45. 669	45. 664	7. 5	7. 5
34. 130	34. 130	45. 240	45. 240	13	13. 2

2- Maysan Region

- **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude, the number of recorded earthquake events, number of events (882) selected for training, and number of events (376) selected for testing. Table (4. 14) shows the result of predicting earthquake's time and magnitude for the Maysan region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 175 sample. **Dt** represents the event where the predict of time only is True and it was 101 sample. **Mg** represents the event where the predict of magnitude only is True and it was 74 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 77 sample and the accuracy is 79%.

- **Predicting the earthquake's time, magnitude, and location:**

Table (4. 15) shows the result of predicting earthquake's time, magnitude and location for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 24 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 34 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 180 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 127 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was 11 sample and the accuracy is 81%.

❖ **Predicting the earthquake's time, magnitude, location and depth**

Table (4. 16) shows the result of predicting earthquake's time, magnitude, location, and depth for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 25 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 33 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 113 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 120 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 82 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 3 samples and the accuracy is 83%.

Table 4. 14: Describe dataset of predict the earthquake's time and magnitude in Maysan using FFNN.

.

Items	Values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of **DtMg**	175
No. of **Dt**	101
No. of **Mg**	74
No. **I**	77
Accuracy	0. 79

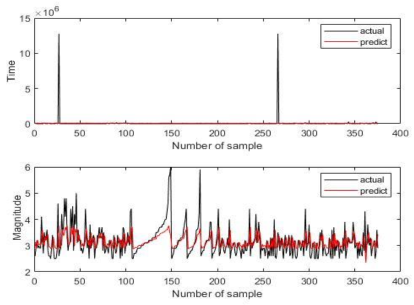
Table 4. 15: Describe dataset of predict the earthquake's time, magnitude and location in Maysan using FFNN.

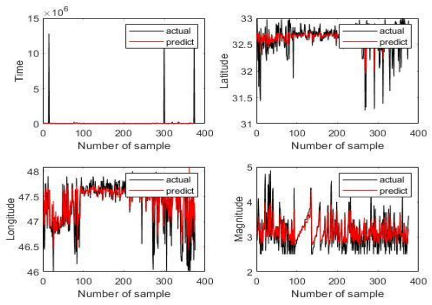
Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	27
No. of Two variables correct **S2**	34
No. of three variables correct **S3**	180
No. of four variables correct **S4**	127
No. of all variables incorrect **I**	11
Accuracy	0. 81

Table 4. 16: Describe dataset of predict the earthquake's time, magnitude, location and depth in Maysan using FFNN.

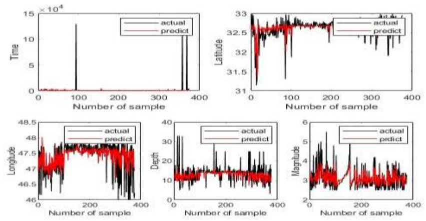
Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	25
No. of Two variables correct **S2**	33
No. of three variables correct **S3**	113
No. of four variables correct **S4**	120
No. of five variables correct **S5**	82
No. of all variables incorrect **I**	3
Accuracy	0. 83

Figure (4:2) shows the actual values and predicted values of earthquake characteristics





(a) time, magnitude (b) time, magnitude, location



(c) time, magnitude location, depth

Figure 4:2 Prediction of the earthquake characteristics of Maysan using FFNN

Figure (4:2) shows the prediction of earthquake characteristics, where 4:2 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Maysan region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples, and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude, and earthquake location variables for the test data Maysan region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth, and earthquake location variables for the test data Maysan region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, the x-axis represents the number of test samples for the variables, and the y- axis represents the values of the variables.

The actual values and predicted values of earthquake characteristics, (time, magnitude, location, depth) for the Maysan region testing dataset as shown in table (4. 17),these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations come with a slight difference from the real values

Table 4. 17: Prediction of the earthquake characteristics of Maysan using FFNN.

Time Actual		Time Predict		Magnitude Actual	Magnitude Predict
18921		18889		3	3
19240		19242		3. 1	3. 3
58273		57943		3. 2	3. 2
74064		69125		4	3. 9
6368		6368		3. 6	3. 6
Location latitude		Location Longitude		Depth Actual	Depth predict
Actual	predict	Actual	predict		
32. 595	32. 590	46. 788	46. 792	10	10. 3
32. 634	32. 629	46. 791	46. 797	3. 2	3. 2
32. 651	32. 648	46. 331	46. 331	10	10
32. 610	32. 610	47. 589	47. 576	3	2. 9
32. 732	32. 738	47. 110	47. 110	5	4. 8

3-Wasit Region

- **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude. the number of recorded earthquake events, the number of events (620) selected for training and the number of events (265) selected for testing. Table (4. 18) shows the result of predicting earthquake's time and magnitude for the Wasit region where the **DtMg** represents the event where the prediction of time and magnitude is True and it was 122 samples. **Dt** represents the event where the prediction of time only is true and it was 27 samples. **Mg** represents the event where the prediction of magnitude only is true and it was 41 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 75 sample and the accuracy is 71%.

- **Predicting the earthquake's time, magnitude and location:**

Table (4. 19) shows the result of predicting the earthquake's time, magnitude and location for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 21 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 32 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 81 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 122 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 9 samples and the accuracy is 76%.

- **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 20) shows the result of predicting earthquake's time, magnitude, location and depth for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 16 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 42 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 101 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 38 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 66 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 4 samples and the accuracy is 77%.

Table 4. 18: Describe dataset of predict the earthquake's time and magnitude in Wasit using FFNN.

Items	Values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of **DtMg**	122
No. of **Dt**	27
No. of **Mg**	41
No. **I**	75
Accuracy	0. 71

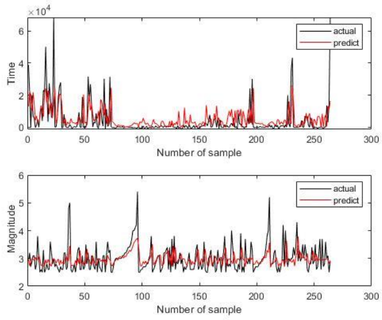
Table 4. 19: Describe dataset of predict the earthquake's time, magnitude, and location in Wasit using FFNN.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	21
No. of Two variables correct **S2**	32
No. of three variables correct **S3**	81
No. of four variables correct **S4**	122
No. of all variables incorrect **I**	9
Accuracy	0. 76

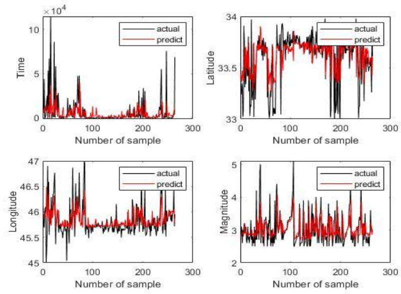
Table 4. 20: Describe dataset of predict the earthquake's time, magnitude, location and depth in Wasit using FFNN.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	16
No. of Two variables correct **S2**	42
No. of three variables correct **S3**	101
No. of four variables correct **S4**	38
No. of five variables correct **S5**	66
No. of all variables incorrect **I**	4
Accuracy	0. 77

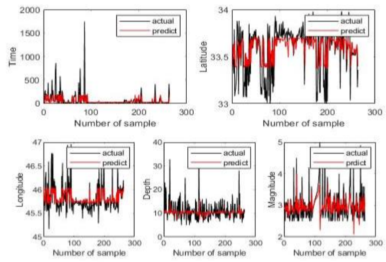
Figure (4:3) shows the actual values and predicted values of earthquake characteristics



(a) time, magnitude



(b) time, magnitude, location



(c) time, magnitude location, depth

Figure 4:3 prediction of earthquake characteristics for Wasit using FFNN.

Figure (4:3) shows the prediction of earthquake characteristics, where 4:1 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Wasit region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude and earthquake location variables for the test data Wasit region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth and earthquake location variables for the test data Wasit region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables

The actual values and predicted values of earthquake characteristics, (time, magnitude, location and depth) for the Wasit region testing dataset as shown in table (4:21),these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations come with a slight difference from the real values.

Table 4. 21: Prediction of the earthquake characteristics of Wasit using FFNN.

Time Actual		Time Predict		Magnitude Actual	Magnitude Predict
10609		11318		2. 8	2. 9
11322		11322		3. 5	3. 5
15628		16432		2. 8	3
13125		13125		3. 1	3. 1
8461		8451		4	3. 8
Location latitude		Location Longitude		Depth Actual	Depth predict
Actual	predict	Actual	predict		
33. 688	33. 688	45. 340	45. 338	7	7. 2
33. 651	33. 694	45. 330	45. 348	11. 5	11. 5
33. 200	33. 200	45. 410	45. 410	9	8. 8
33. 699	33. 702	46. 005	46. 012	10	10
33. 220	33. 220	46. 180	46. 180	13. 7	13. 6

The accuracy for each region to predict earthquake characteristics for the two variables (time and magnitude), four variables (time, magnitude, longitude and latitude) and five variables (time, magnitude, longitude, latitude and depth) as shown in table (4. 22).

Table 4. 22: Accuracy of earthquake prediction using FFNN.

First Hidden layer (no. Of neuron)	Second Hidden layer (no. Of neuron)	Accuracy of Sulaymaniyah			Accuracy of Maysan			Accuracy of Wasit		
		Predict two variable	Predict four variable	Predict five variable	Predict two variable	Predict four variable	Predict five variable	Predict two variable	Predict four variable	Predict five variable
13	26	71%	74%	77%	76%	79%	82%	68%	71%	74%
13	31	74%	76%	79%	75%	78%	79%	67%	73%	76%
13	35	72%	73%	77%	78%	79%	80%	69%	74%	75%
17	26	74%	75%	78%	78%	80%	81%	70%	73%	74%
17	31	76%	78%	79%	77%	79%	83%	69%	75%	77%
17	35	75%	77%	80%	76%	80%	81%	71%	74%	76%
20	26	75%	76%	79%	77%	78%	81%	68%	72%	75%
20	31	73%	75%	81%	76%	77%	82%	67%	75%	76%
20	35	76%	78%	81%	79%	81%	83%	71%	76%	77%

Table (4. 22) shows the results using FFNN to predict the magnitude, time, location and depth using the gradient descent training algorithm, two hidden layers where a different number of neurons are tested in each layer, in the first layer (13, 17, 20) and the second layer (26, 31, 35) and achieved a good result in use (20 neurons in first hidden layer and 35 in second hidden layer). Where the increase in accuracy of the prediction by increase in the number of earthquake characteristics due to the interdependence and relationship of variables, where the magnitude of the earthquake is related to the location and depth because of the terrain of the region. The prediction of time, location, magnitude and depth achieved higher accuracy than prediction of time and magnitude and higher than prediction of time, magnitude and location.

4.4 Earthquake prediction using LSTM

1- AL Sulaymaniyah Region

- **Predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude. the number of recorded earthquake events, the number of events (942) selected for training and the number of events (403) selected for testing. Table (4. 23) shows the result of predicting earthquake's time and magnitude for the Sulaymaniyah region where the **DtMg** represents the event where the prediction of time and magnitude is true and it was 220 sample. **Dt** represents the event where the prediction of time only is true and it was 50 samples. **Mg** represents the event where the prediction of magnitude only is true and it was 53 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 80 sample and the accuracy is 80%.

- **Predicting the earthquake's time, magnitude and location:**

Table (4. 24) shows the result of predicting earthquake's time, magnitude and location for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 30 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 35 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 198 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 136 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was 4 samples and the accuracy is 82%.

❖ **predicting the earthquake's time, magnitude, location and depth:**

Table (4. 25) shows the result of predicting earthquake's time, magnitude, location and depth for the Sulaymaniyah region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 23 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 30 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 70 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 162 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 118 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 0 sample and the accuracy is 86%.

Table 4. 23: Describe dataset of predicting the earthquake's time and magnitude in Sulaymaniyah using LSTM.

Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of **DtMg**	220
No. of **Dt**	50
No. of **Mg**	53
No. **I**	80
Accuracy	0. 80

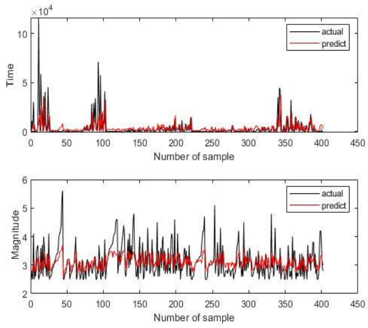
Table 4. 24: Describe dataset of predicting the earthquake's time, magnitude and location in Sulaymaniyah using LSTM.

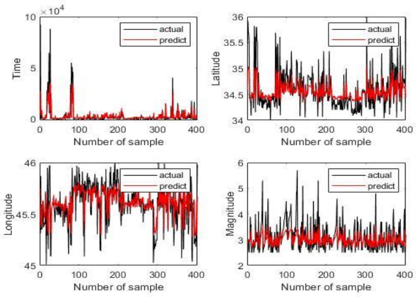
Items	values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	30
No. of Two variables correct **S2**	35
No. of three variables correct **S3**	198
No. of four variables correct **S4**	136
No. of all variables incorrect **I**	4
Accuracy	0. 82

Table 4. 25: Describe dataset of predicting the earthquake's time, magnitude, location and depth in Sulaymaniyah using LSTM.

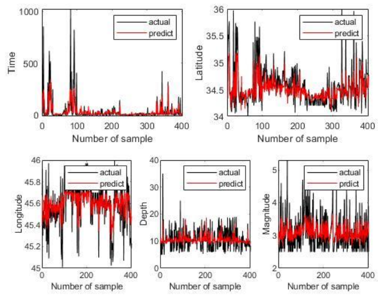
Items	Values
No. of all instances	1345
No. of training set	942
No. of testing set	403
No. of one variable correct **S1**	23
No. of Two variables correct **S2**	30
No. of three variables correct **S3**	70
No. of four variables correct **S4**	162
No. of five variables correct **S5**	118
No. of all variables incorrect **I**	0
Accuracy	0. 86

Figure (4:4) shows the actual values and predicted values of earthquake characteristics





(a) time, magnitude, (b) time, magnitude, location



(c) time, magnitude, location, depth

Figure 4:4 Prediction of earthquake characteristics of Sulaymaniyah using LSTM.

Figure (4:4) shows the prediction of earthquake characteristics, where 4:1 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Sulaymaniyah region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude and earthquake location variables for the test data in the Sulaymaniyah region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth and earthquake location variables for the test data Sulaymaniyah region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y- axis represents the values of the variables.

The actual and predicted values of earthquake characteristics, (time, magnitude, location and depth) for the Sulaymaniyah region testing dataset as shown in table (4:26), these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations come with a slight difference from the real values.

Table 4. 26: Prediction of earthquake characteristics of the Sulaymaniyah using LSTM

Time Actual		Time Predict		Magnitude Actual	Magnitude Predict
30472		30328		2. 9	2. 9
52142		51835		3	3. 1
15876		15876		2. 8	2. 9
11088		11088		2. 8	2. 8
62985		63021		3. 1	3. 1
Location latitude		Location Longitude		Depth Actual	Depth predict
Actual	predict	Actual	predict		
34. 438	34. 441	45. 538	45. 540	10	10
34. 598	34. 601	45. 114	45. 118	12	11. 10
34. 346	34. 350	45. 524	45. 524	9	9
34. 411	34. 411	45. 581	45. 581	11	11
34. 602	34. 602	45. 731	45. 733	17	16. 6

2- Maysan Region

❖ **predicting the earthquake's time and magnitude:**

To predict the earthquake's time and magnitude, the number of recorded earthquake events, the number of events (882) selected for training and the number of events (376) selected for testing. Table (4. 27) shows the result of predicting earthquake's time and magnitude for the Maysan region where the **DtMg** represents the event where the prediction of time and magnitude is true and it was 244 samples. **Dt** represents the event where the prediction of time only is true and it was 43 samples. **Mg** represents the event where the prediction of magnitude only is true and it was 38 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 51 sample and the accuracy is 87%.

❖ **Predicting the earthquake's time, magnitude and location:**

Table (4. 28) shows the result of predicting the earthquake's time, magnitude and location for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 21 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 22 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 189 samples. S4 represents the event where the prediction of all of the earthquake characteristics are true and it was 139 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 5 samples and the accuracy is 88%.

❖ **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 29) shows the result of predicting earthquake's time, magnitude, location and depth for the Maysan region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 12 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 20 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 110 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 125 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 109 samples. **I** represent the event in which the prediction of all the earthquake characteristics are false and it was 0 sample and the accuracy is 91%.

Table 4. 27: Describe dataset of predicting the earthquake's time and magnitude in Maysan using LSTM.

Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of **DtMg**	244
No. of **Dt**	43
No. of **Mg**	38
No. **I**	51
Accuracy	0. 87

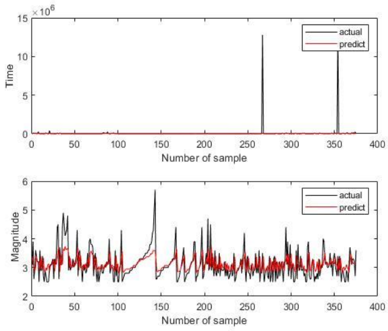
Table 4. 28: Describe dataset of predicting the earthquake's time, magnitude and location in Maysan using LSTM.

Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	21
No. of Two variables correct **S2**	22
No. of three variables correct **S3**	189
No. of four variables correct **S4**	139
No. of all variables incorrect **I**	5
Accuracy	0. 88

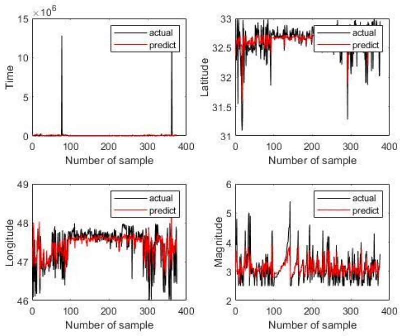
Table 4. 29: Describe dataset of predicting the earthquake's time, magnitude, location and depth in Maysan using LSTM.

Items	values
No. of all instances	1258
No. of training set	882
No. of testing set	376
No. of one variable correct **S1**	12
No. of Two variables correct **S2**	20
No. of three variables correct **S3**	110
No. of four variables correct **S4**	125
No. of five variables correct **S5**	109
No. of all variables incorrect **I**	0
Accuracy	0. 91

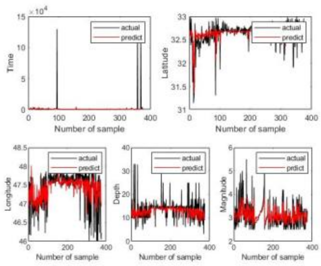
Figure (4:5) shows the actual values and predicted values of earthquake characteristics



(a) time, magnitude



(b) time, magnitude, location



(c) time, magnitude location, depth

Figure 4:5 Prediction of earthquake characteristics of Maysan using LSTM.

Figure (4:5) shows the prediction of earthquake characteristics, where 4:1 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Maysan region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude and earthquake location variables for the test data Maysan region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth and earthquake location variables for the test data Maysan region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y- axis represents the values of the variables.

The actual values and predicted values of earthquake characteristics, (time, magnitude, location, depth) for the Maysan region testing dataset as shown in table (4. 30).), these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations come with a slight difference from the real values

Table 4. 30: Prediction of the earthquake characteristics of Maysan using LSTM

<table>
<tr><th colspan="2">Time Actual</th><th colspan="2">Time Predict</th><th>Magnitude Actual</th><th>Magnitude Predict</th></tr>
<tr><td colspan="2">17522</td><td colspan="2">17554</td><td>3. 1</td><td>3</td></tr>
<tr><td colspan="2">39272</td><td colspan="2">39272</td><td>3</td><td>3</td></tr>
<tr><td colspan="2">58273</td><td colspan="2">57943</td><td>2. 9</td><td>2. 9</td></tr>
<tr><td colspan="2">17159</td><td colspan="2">17203</td><td>4. 1</td><td>3. 9</td></tr>
<tr><td colspan="2">14654</td><td colspan="2">14672</td><td>3. 5</td><td>3. 5</td></tr>
<tr><th colspan="2">Location latitude</th><th colspan="2">Location Longitude</th><th rowspan="2">Depth Actual</th><th rowspan="2">Depth predict</th></tr>
<tr><th>Actual</th><th>predict</th><th>Actual</th><th>predict</th></tr>
<tr><td>32. 574</td><td>32. 573</td><td>46. 088</td><td>46. 093</td><td>10</td><td>10. 4</td></tr>
<tr><td>32. 622</td><td>32. 625</td><td>46. 014</td><td>46. 014</td><td>9</td><td>9</td></tr>
<tr><td>32. 573</td><td>32. 578</td><td>47. 091</td><td>46. 089</td><td>10</td><td>10</td></tr>
<tr><td>32. 114</td><td>32. 114</td><td>47. 679</td><td>47. 678</td><td>3</td><td>3. 1</td></tr>
<tr><td>32. 222</td><td>32. 222</td><td>47. 006</td><td>47. 006</td><td>6</td><td>6</td></tr>
</table>

2- Wasit Region

❖ Predicting the earthquake's time and magnitude:

To predict the earthquake's time and magnitude, the number of recorded earthquake events, the number of events (620) selected for training and the number of events (265) selected for testing. Table (4. 31) shows the result of predicting the earthquake's time and magnitude for the Wasit region where the **DtMg** represents the event where the prediction of time and magnitude is true and it was 128 sample. **Dt** represents the event where the prediction of time only is true and it was 32 samples. **Mg** represents the event where the prediction of magnitude only is true and it was 43 samples. **I** represent the event where the predicting the earthquake's time and magnitude are wrong and was 62 sample and the accuracy is 76%.

- **Predicting the earthquake's time, magnitude and location:**

Table (4. 32) shows the result of predicting the earthquake's time, magnitude and location for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 18 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 32 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 133 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 77 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 5 samples and the accuracy is 79%.

- **Predicting the earthquake's time, magnitude, location and depth:**

Table (4. 33) shows the result of predicting the earthquake's time, magnitude, location and depth for the Wasit region where **S1** represents the event in which the prediction of one of the earthquake characteristics is true and it was 13 samples. **S2** represents the event in which the prediction of two from the characteristics of the earthquake is true and it was 27 samples. **S3** represents the event in which the prediction of three from the characteristics was true and it was 72 samples. **S4** represents the event where the prediction of all of the earthquake characteristics are true and it was 65 samples. **S5** represents the event where the prediction of all of the earthquake characteristics are true and it was 88 samples. **I** represent the event in which prediction of all the earthquake characteristics are false and it was 0 sample and the accuracy is 84%. Figure (4:6) shows the actual and predicted values of earthquake characteristics

Table 4. 31: Describe dataset of predicting the earthquake's time and magnitude in Wasit using LSTM

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of **DtMg**	128
No. of **Dt**	32
No. of **Mg**	43
No. **I**	62
Accuracy	0. 76

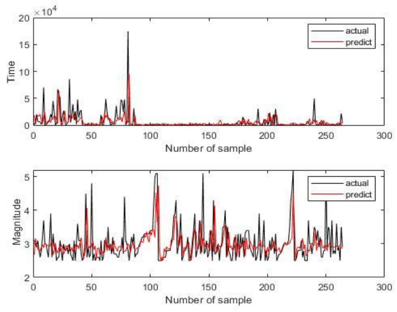
Table 4. 32: Describe dataset of predicting the earthquake's time, magnitude and location in Wasit using LSTM.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	18
No. of Two variable correct **S2**	32
No. of three variable correct **S3**	133
No. of four variable correct **S4**	77
No. of all variable incorrect **I**	5
Accuracy	0. 79

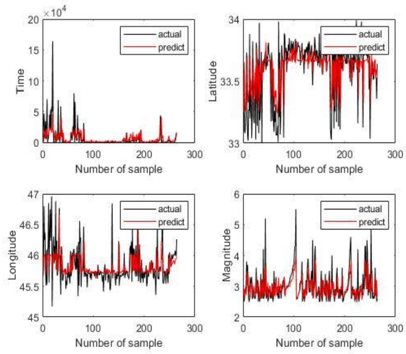
Table 4. 33: Describe dataset of predict the earthquake's time, magnitude, location and depth in Wasit using LSTM.

Items	values
No. of all instances	885
No. of training set	620
No. of testing set	265
No. of one variable correct **S1**	13
No. of Two variables correct **S2**	27
No. of three variables correct **S3**	72
No. of four variables correct **S4**	65
No. of five variables correct **S5**	88
No. of all variables incorrect **I**	0
Accuracy	0. 84

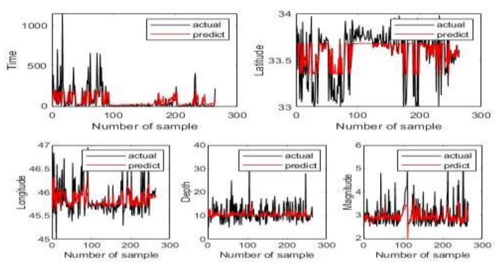
Figure (4:6) shows the actual and predicted values of earthquake characteristics



(a) time, magnitud



(b) time, magnitude, location



(c) time, magnitude location, depth

Figure 4:6 Prediction of earthquake characteristics of Wasit using LSTM.

Figure (4:6) shows the prediction of earthquake characteristics, where 4:6 (a) represents the expected and real values of the time and earthquake magnitude variables for the test data of the Wasit region. Where the black color represents the real values, the red color represents the expected values, the x-axis represents the number of test samples and the y- axis represents the values of the two variables. (b) represents the expected and real values of the time, magnitude and earthquake location variables for the test data Wasit region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables. (c) represents the expected and real values of the time, magnitude, depth and earthquake location variables for the test data Wasit region. Where the black color represents the real values of the variable, the red color represents the expected values of the variable, and the x-axis represents the number of test samples for the variables, and the y-axis represents the values of the variables.

The actual values and predicted values of earthquake characteristics, (time, magnitude, location and depth) for the Wasit region testing dataset as shown in table (4:34), these columns represent some samples of the test data some expectations are completely identical to the real values and some expectations come with a slight difference from the real values.

Table 4. 34: Prediction of earthquake characteristics of Wasit using LSTM.

Time Actual		Time Predict		Magnitude Actual	Magnitude Predict
25249		24988		3	2. 9
49281		49281		3. 5	3. 4
13077		12860		2. 7	2. 7
31924		32095		3	3
14565		14565		2. 8	2. 8
Location latitude		Location Longitude		Depth Actual	Depth predict
Actual	Predict	Actual	predict		
33. 498	33. 499	45. 340	45. 348	10	10. 1
33. 718	33. 718	45. 430	45. 430	11	10. 9
33. 200	33. 200	45. 113	45. 113	10. 6	10. 7
33. 210	33. 208	46. 204	46. 205	10. 5	10. 5
33. 010	33. 22	46. 090	45. 086	10	10

The accuracy for each region to predict earthquake characteristics for the two variables (time and magnitude), four variables (time, magnitude, longitude and latitude) and five variables (time, magnitude, longitude, latitude and depth) as shown in table (4. 35).

Table 4. 35: Accuracy of earthquake prediction using LSTM.

No	Train algorithm	LSTM Hidden Unit	Dropout Prob.	Accuracy of Sulaymaniyah			Accuracy of Maysan			Accuracy of wasit		
				Predict Two Var.	Predict four Var.	Predict five Var.	Predict Two Var.	Predict four Var.	Predict five Var.	Predict Two Var.	Predict four Var.	Predict five Var.
1	Rmsprop	100	0. 1	74%	79%	82%	82%	84%	86%	72%	76%	80%
2		100	0.2	76%	78%	81%	85%	85%	85%	76%	78%	81%
3		100	0.5	75%	77%	85%	83%	87%	89%	74%	75%	83%
4		150	0.1	78%	80%	84%	81%	84%	88%	77%	79%	87%
5		150	0. 2	77%	81%	83%	85%	86%	90%	75%	78%	84%
6		150	0. 5	76%	78%	79%	80%	83%	85%	74%	75%	79%
7		200	0. 1	79%	80%	85%	83%	85%	87%	75%	77%	82%
8		**200**	**0. 2**	**80%**	**82%**	**86%**	**87%**	**88%**	**91%**	**76%**	**79%**	**84%**
9		200	0. 5	78%	82%	84%	84%	85%	86%	72%	76%	81%

Table (4. 35) shows the results using the LSTM to predict the magnitude, time, location and depth using the Rmsprop training algorithm and two hidden layers where a different number of hidden units are tried in each layer (100, 150, 200 units) and the probability of dropout (0. 1, 0. 2, 0. 5) to get a balanced, more efficient and accurate network, it achieved a better result in (200 hidden unit in each hidden layer and 0. 2 probability of dropout). LSTMs algorithm achieved high accuracy because of the ability to capture non-linear relationships more efficiently.

Mean square error of the model's performance to predict earthquakes characteristics, using the algorithm of SVR, FFNN and LSTM. As shown in table (4. 36). The results show that the relationship of the variables decreases the MSE of the model as the greater the number of variables related to one event, be better depending on the magnitude and location of the earthquake. And that the LSTM algorithm can deal with sequential events greater.

Table 4. 36: MSE of earthquake prediction using SVR,FFNN and LSTM.

Region	Type of prediction	MSE using SVR	MSE using FFNN	MSE using LSTM
Sulaymaniyah	Time & magnitude	0. 0866	0. 0541	0. 0382
	Time, magnitude & location (latitude, longitude)	0. 0853	0. 0521	0. 0364
	Time, magnitude, location (latitude, longitude) & depth	0. 0794	0. 0375	0. 0292
Maysan	Time & magnitude	0. 0744	0. 0493	0. 0283
	Time, magnitude & location (latitude, longitude)	0. 0655	0. 0372	0. 0274
	Time, magnitude, location (latitude, longitude) & depth	0. 0622	0. 0351	0. 0223
Wasit	Time & magnitude	0. 0914	0. 0595	0. 0543
	Time, magnitude & location (latitude, longitude)	0. 0877	0. 0532	0. 0481
	Time, magnitude, location (latitude, longitude) & depth	0. 0811	0. 0512	0. 0342

4. 5 Discussion

The result obtained from applying the algorithms to different data where LSTM algorithm achieves greater accuracy than SVR and FFNN algorithm in predicting Time and Magnitude, where SVR achieved an accuracy of 69% and FFNN achieved an accuracy of 76% ,while LSTM achieved an accuracy of 80% using the data of the Sulaymaniyah region, SVR algorithm achieved an accuracy of 70% and FFNN achieved an accuracy of 79 while LSTM achieved an accuracy of 87% using Maysan data. In the Wasit region, SVR achieved an accuracy of 61% and FFNN achieved an accuracy of 71, while the accuracy of the LSTM was 76%. As shown in figure (4. 7).This is because SVR is not able to deal with large and complex data, while FFNN and LSTM is more efficient in dealing with complex and non-linear data.

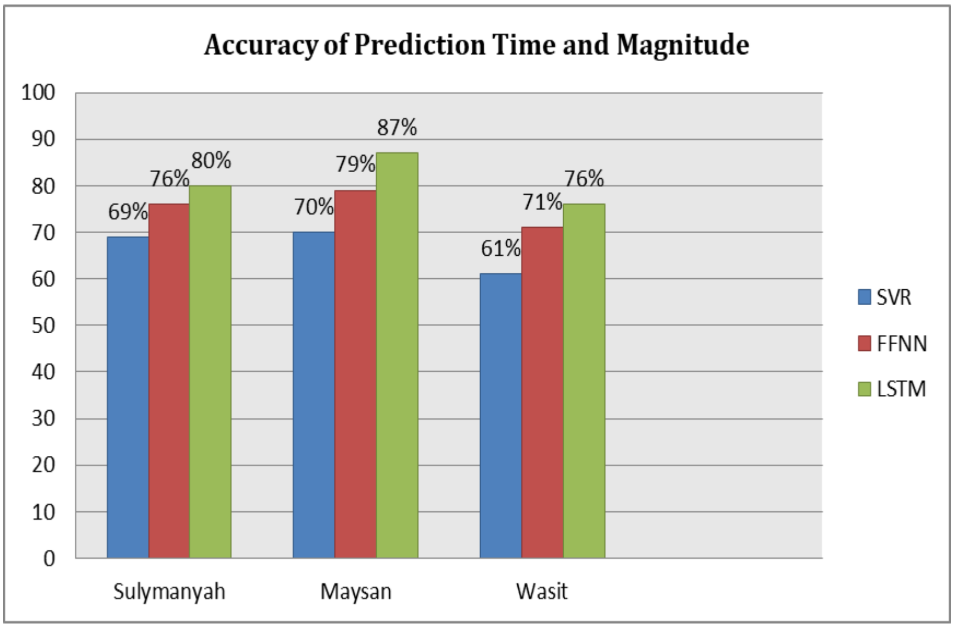


Figure 4. 7: Accuracy rate for predict Time and Magnitude

Higher accuracy was achieved in the prediction of time, magnitude and location due to the interrelationship of seismic characteristics and low total error rate **I** where was equal to 12 using FFNN and equal to 4 by LSTM in Sulaymaniyah region where the accuracy 0.78% by FFNN and 82% by LSTM, while SVR performance was is low , where **I** equal to 32 and the accuracy 71%. In the Maysan region, the accuracy of FFNN was 81% and **I** equal to 11 and the LSTM algorithm achieved an accuracy of 88% and **I** equal to 4,while

SVR performance was is low , where **I** equal to 26 and the accuracy 72%.In the Wasit region, the FFNN algorithm achieved an accuracy of 76% and **I** equal to 9, while the LSTM algorithm achieved an accuracy of 79% and **I** equal to 5, while SVR performance was is low , where **I** equal to 37 and the accuracy 63%. As shown in figure (4. 8).

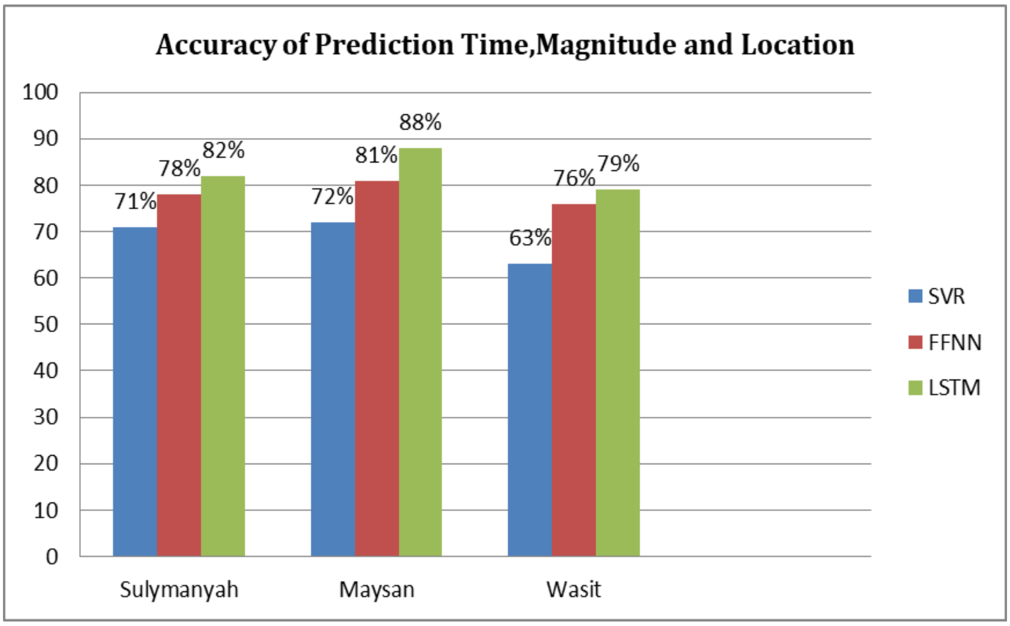


Figure 4. 8: Accuracy rate for predicting Time, Magnitude and Location

In predicting time, magnitude, location and depth, the LSTM and FFNN algorithm achieved higher accuracy than SVR, where the decrease in the number of events in which all the variables are incorrect (I) to zero in Maysan, Wasit and Sulaymaniyah; very few number of event where all variable incorrect (I) by using FFNN and An increase in the number of events in which all the variables are true. In the Sulaymaniyah region, the accuracy of the FFNN algorithm reached 81% and the accuracy of the LSTM algorithm was 86%, while SVR was 72%. In Maysan region, the accuracy using the FFNN algorithm reached 83% and it was 91% using the LSTM algorithm, while SVR was 73%. As for the Wasit region, the accuracy of FFNN reached 77%, while the LSTM algorithm achieved an accuracy of 84%,while SVR was 66%. As shown in figure (4. 9).

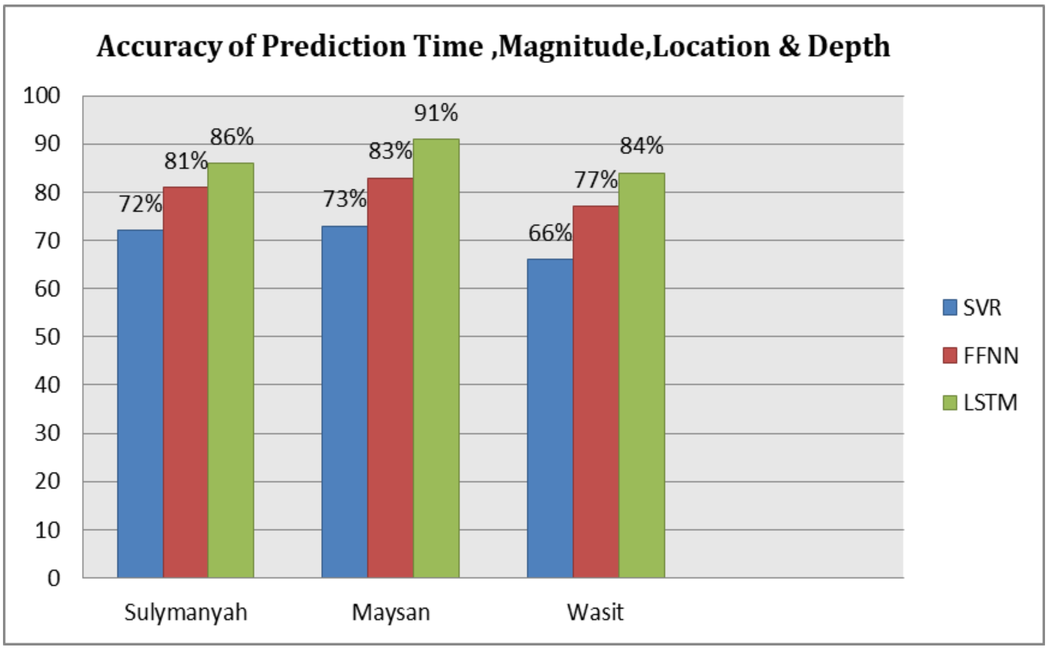


Figure 4. 9: Accuracy rate for predicting Time, Magnitude, Location &Depth

The accuracy of predicting the earthquake's time, magnitude, location and depth using FFNN and LSTM and the number of incorrect samples (predict of all variables was incorrect) shows in table (4. 37).

Table 4. 37: Accuracy of earthquake prediction using SVR, FFNN and LSTM.

Region	Type of prediction	Values of **I** with SVR	Values of **I** with FFNN	Values of **I** with LSTM	Acc. using SVR	Acc. using FFNN	Acc. using LSTM
Sulaymaniyah	Time and magnitude	121	93	80	69%	76%	80%
	Time, magnitude, and location	32	12	4	71%	78%	82%
	Time, magnitude, location and depth	20	7	0	72%	81%	86%
Maysan	Time and magnitude	111	77	51	70%	79%	87%
	Time, magnitude and location	26	11	4	72%	81%	88%
	Time, magnitude, location and depth	18	3	0	73%	83%	91%
Wasit	Time and magnitude	103	75	62	61%	71%	76%
	Time, magnitude and location	37	9	5	63%	76%	79%
	Time, magnitude, location and depth	28	4	0	66%	77 %	84%

4. 6 Comparison with Literature

There are many researches in the field of earthquake prediction using learning techniques and earthquake data sets according to the study area and earthquake characteristics selected. Table (4. 38) illustrates the comparison with the researches of earthquake prediction.

Table 4. 38: Comparison with other literature.

Ref	Algorithms	Type of prediction	Accuracy
Narayanakumar and Raja [14].	BPNN	The magnitude of a moderate earthquake	75%
		The magnitude of a small earthquake	66.66%
Zhou et al [15].	ANN-SVR	Magnitude	73.37%
Saba S, Ahsan F, et al [18].	FFNN	Time & magnitude	78%
	BAT-ANN	Time & magnitude	85.37%
Proposed algorithm	SVR	Magnitude	67%
		Time & magnitude	70%
		Time, magnitude & location	72%
		Time, magnitude, location & depth	73%
	FFNN	Magnitude	74%
		Time & magnitude	79%
		Time, magnitude & location	81%
		Time, magnitude, location depth	83%
	LSTM	Magnitude	83%
		Time & magnitude	87%
		Time, magnitude & location	88%
		Time, magnitude, location & depth	91%

CHAPTER FIVE

Conclusion & Future Work

CHAPTER FIVE

5.1 Introduction

In this chapter, the conclusions of the results which are obtained from the Implementation the algorithms of machine learning can be represented, which shown the best system can be used for earthquake prediction. In addition, this chapter discusses future work and ideas that might be applied for earthquake prediction.

5. 2 Conclusion

The obtained results by applying the machine learning algorithms(support vector regression), (feed forward neural network) and deep Learn (long short term memory) algorithm for predicting the earthquake's characteristics and the conclusions are summarized below:

1. LSTM model can be used as the best model for earthquake prediction, the results show superior performance for all metrics as compared with other models, which achieve accuracy in predict time and magnitude of 87% using the dataset of Maysan region, in predict earthquake time, magnitude and location achieved an accuracy of 88%, and in predict time, magnitude, location, depth achieved accuracy of 91%.
2. LSTM is optimized neural network that can handle issues of exploding and vanishing gradients.
3. Data processing to reduce differences between data it is beneficial for enhancing the learning process.
4. The most essential component that determines the results of proposed algorithms is chosen proper learning rate and training algorithm.
5. The results show that the relationship of the variables increases the accuracy of the model, subsequently many of variables related to one event gives better accuracy.

5. 3 Future work

In this thesis, certain learning technique is used for earthquakes prediction and obtained good results, there are many ideas that suggestions of the future works mentioned below:

1. Use other algorithms of machine learning and deep learning techniques for earthquake prediction.
2. Use different datasets to evaluate the proposed system.
3. The search for factors related to earthquake prediction and their addition to the seismic dataset must continue.

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الخلاصة

الزلازل هي كارثة طبيعية ناتجة عن حركة الصفائح التكتونية بسبب إطلاق الطاقة الداخلية الهائلة، يمكن أن تسبب الزلازل إصابات خطيرة ووفيات، وتدمر الهياكل والبنية التحتية الضخمة مما يؤدي إلى خسائر اقتصادية كبيرة. تنبؤات الزلازل تحقق سلامة المجتمع وتقلل من حجم الدمار. للتنبؤ بوقت الزلزال وحجمه وعمقه وموقعه، تم اقتراح مجموعة متنوعة من التقنيات، مثل التحليل الإحصائي والرياضي والتحقيق في الإشارات للسلائف الزلزالية وبسبب الطابع الديناميكي الظاهري للزلزال، فإنها عادة لا تسفر عن نتائج ممتازة. اكتسبت قدرة الذكاء الاصطناعي على اكتشاف الأنماط الخفية للبيانات والعلاقة غير الخطية اهتمامًا كبيرا في السنوات الأخيرة. تم استخدامه في عدة مجالات وحقق نتائج إيجابية. تستخدم هذه الرسالة خوارزميات الذكاء الاصطناعي في التنبؤ بالزلازل القادمة لاتخاذ الاحتياطات اللازمة وتقليل المخاطر في المناطق المعرضة للزلازل. تم تطبيق خوارزميات التعلم الآلي Support Vector Regression و Feed Forward Neural Network و Long Short Term Memory للتنبؤ بحدوث الزلزال القادم بناءً على البيانات التاريخية التي تم الحصول عليها من المديرية العامة للأنواء الجوية والرصد الزلزالي في العراق، من خلال بيانات الدراسة لثلاث مناطق مختلفة في العراق (السليمانية ،ميسان وواسط) للتنبؤ بخصائص الزلزال (الوقت، القوة، الموقع والعمق) وتقييم أداء التنبؤ باستخدام بيانات الاختبار.

تمت مقارنة النتائج التي تم الحصول عليها من خلال مقاييس التقييم لتحديد الخوارزمية الأفضل للتنبؤ بالزلازل. من هذه النتائج ، استنتج أن Long Short Term Memory هي الأفضل في التنبؤ بخصائص الزلازل وحققت نتائج واعدة، لأن Long Short Term Memory شبكة عصبية محسّنة يمكنها التعامل مع مشكلة انفجار وتلاشي التدرجات، حيث حققت دقة 87٪ في التنبؤ بوقت الزلزال وقوته، و دقة 88٪ في توقع وقت الزلزال، قوته وموقعه ، و 91٪ دقة في التنبؤ بقوة الزلزال، موقعه، وقته وعمقه

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التنبؤ بالزلازل اعتماداً على تقنيات التعلم الآلي

رسالة مقدمة الى

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وهي جزء من متطلبات نيل درجة الماجستير في علوم الحاسبات

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