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A Hybrid Early Earthquake Prediction Model Using IoT Networks and Deep Learning Algorithms

Mohammed Al Yousef[1], Dr. Amir Jalali Bidgoli[2]

[1]*Email: mohammed.alyousef@uobabylon.edu.iq,* [2]*Email: jalaly@qom.ac.ir*

[1,2] *University of Qom, Department of Information Technology Engineering, Iran*

Abstract

Earthquakes are one of the most serious natural disasters that threaten human life and property, which makes their early prediction extremely important to reduce their devastating effects. This research aims to develop an intelligent earthquake prediction system based on the integration of Internet of Things (IoT) technologies with deep learning algorithms, specifically recurrent neural networks (RNN) and long-term short-term memory networks (LSTM). The methodology was developed by collecting Earthquake Data in real time using a network of IoT sensors, where historical real data from the year (1965 to 2021) was used to train the model and process this data using an optimized LSTM model with the use of activation functions (Relu,tanh , Sigmoid) and optimization algorithms (Adam, RMSprop, SGD) . The model was developed using the ReLU activation function with the Adam optimization algorithm to improve the prediction accuracy with Learning Rate is equal to (0.001) and Epochs is equal to (200).. The experimental results showed a high efficiency of the proposed model, achieving a determination coefficient (R2). By (0.9984) with a low MSE error rate of up to (0.0003), which confirms the system's ability to accurately predict earthquakes before they occur. This research makes an important contribution to the field of forecasting natural disasters using artificial intelligence and IoT technologies. These results confirm the possibility of relying on modern technologies in the development of earthquake early warning systems, which opens up new horizons for research in the field of Natural Disaster Risk Reduction and protection of vulnerable communities.

***Keywords**: earthquake prediction,Internet of Things (IoT) deep learning algorithms RNN & LSTM*

1. Introduction

Natural disasters pose significant threats to human life and infrastructure worldwide. This paper focuses on leveraging artificial intelligence (AI) and Internet of Things (IoT) technologies to revolutionize disaster prediction and management, particularly earthquakes. By analyzing vast amounts of data from sensors, weather stations, and social networks, AI can identify patterns that could indicate potential catastrophic events[1].

Historically, earthquake prediction has evolved from basic statistical methods to more sophisticated approaches[2]. The advancement in prediction methods has led to increased attention on economic considerations, particularly the cost-effectiveness of data gathering and preventative measures against potential earthquake damage[3]. Statistical techniques have traditionally been used for long-term risk assessment, but modern approaches focus on medium to short-term forecasting using precursory phenomena such as seismic velocity changes and microearthquake activity

The Internet of Things,[4] coined by Kevin Ashton in 1997, has grown from simple RFID tags to an anticipated trillion connected devices by 2030.the Internet of Things (IoT) applications in smart cities demonstrate its potential for high-quality service delivery and environmental monitoring[5]. The fallowing systems integrate actuation, networking, processing, and sensing components to collect and analyze data for improved urban management and disaster response. Artificial intelligence has made remarkable progress, particularly in machine learning and deep learning[6]. Modern AI systems achieve high accuracy in data analysis, the object recognition, and speech processing[7]. Deep learning, utilizing neural networks with multiple layers, has become particularly effective for complex applications[8]. The integration of AI and IoT technologies offers promising opportunities for improving disaster preparedness and mitigation strategies

This research aims to design an innovative system combining AI and IoT technologies for earthquake prediction. The proposed system utilizes deep learning algorithms, specifically RNN and LSTM, integrated with IoT sensors for data collection and analysis. This stady represents a significant contribution as one of the first attempts to merge AI and IoT applications for earthquake prediction in the Middle East, addressing the persistent challenge of recurring earthquakes.

The results faces several challenges, including data quality and collection issues, system integration complexities, and algorithm optimization. However, the potential benefits of developing an effective earthquake prediction system justify addressing these challenges. Through this research, we aim to contribute to the development of more resilient and safer societies by improving our ability to predict and respond to seismic events.

2. Literature review

Previous research in earthquake prediction using artificial intelligence and Internet of Things technologies has shown promising developments. Several notable studies have explored different approaches to enhance earthquake detection and early warning systems.

Abdalzaher et al. investigated the integration of earthquake early warning systems (EEWS) in smart cities using IoT and machine learning technologies. Their study focused on developing a generic EEWS architecture and classifying ML models for analysis. While their findings demonstrated the potential of integrating IoT and ML for earthquake prediction, they identified challenges such as communication delays between IoT devices and cloud servers, energy consumption issues, and security concerns [9].

Sinha conducted a comprehensive analysis of current earthquake detection methods and prediction techniques. The research examined various existing methods using wireless sensor nodes, IP-based WSN, and IoT technologies. The study focused on analyzing data acquisition techniques and earthquake forecasting methods, highlighting the need for innovative systems to address current shortcomings in detection and prediction.[10]

A significant contribution was made by Pwavodi et al. , who reviewed the challenges and advancements in earthquake prediction using AI and IoT technologies. Their research emphasized the importance of collaboration between seismologists and computer experts. They analyzed over 480 resources and selected 160 articles from high-impact journals, identifying key challenges including computational complexity, data quality issues, and the need for better integration of hydrogeological measurements in AI model training [11].

Wang et al. , explored machine learning methods, particularly random forest and LSTM neural networks, for predicting large earthquakes using seismic features from small earthquakes. Their research demonstrated that random forest performed well in classifying large earthquake occurrences, while LSTM provided accurate estimates of earthquake magnitude. However, they noted limitations in predicting earthquake swarms and the need for longer-term seismic monitoring.[12].

K. C., S. T, G. V , developed the 3S-AE-CNN model for quick and accurate prediction of earthquake parameters. Their model showed promising results in predicting magnitude, latitude, and longitude with minimal errors. The research demonstrated the potential of deep learning models in Early Earthquake Warning Systems (EEWS), although some limitations were noted in areas where the model's performance didn't match benchmarks.[13].

These studies collectively highlight the evolving landscape of earthquake prediction technology, emphasizing the potential of combining AI and IoT solutions while acknowledging the various challenges that need to be addressed for more effective implementation.

3. methods

The proposed research methodology combines IoT technology with deep learning models for earthquake prediction. Here's a comprehensive summary of the approach:

3.1. The System Architecture:

The system consists of two main components:

3.1.1. IoT earthquake sensing and data collection system

3.1.2. Deep Learning model using RNN and LSTM algorithms

3.2. The Data Collection and IoT Sensor Network:

Deployment of high-precision seismometers and accelerometers,, the Real-time data transmission using edge computing, GPS time synchronization for precise temporal alignment, Secure data storage with both local and cloud solutions .

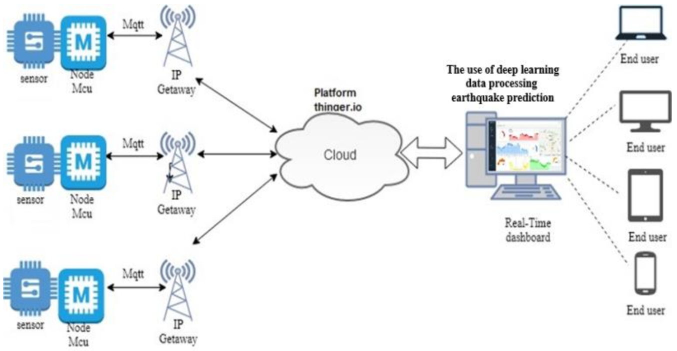

Figure (1) The Data Collection and IoT Sensor Network Setup

3.3. The Data Preprocessing and Feature Extraction:

Data cleaning using band-pass filters , Missing data handling through interpolation techniques

Time series segmentation into fixed-length windows, Feature extraction in time and frequency domains , Statistical feature calculation and normalization

Date	Latitude	Longitude	Depth	Magnitude
1965-01-02	19.246	145.616	131.6	6.0
1965-02-02	1.863	127.352	80.0	5.8
1965-03-02	-20.579	-173.972	20.0	6.2
1965-04-02	-59.076	-23.557	15.0	5.8
1965-05-02	11.938	126.427	15.0	5.8
...	...	...	...	...
2021-12-27	12.434	143.987	5.8	5.5
2021-12-28	-59.438	-151.353	10.0	5.7
2021-12-29	9.954	-84.313	72.8	5.9
2021-12-30	37.396	141.341	35.0	6.1
2021-12-31	36.409	70.748	207.3	5.9

20788 rows × 4 columns

Figure (2) Snapshot of dataset Preprocessing

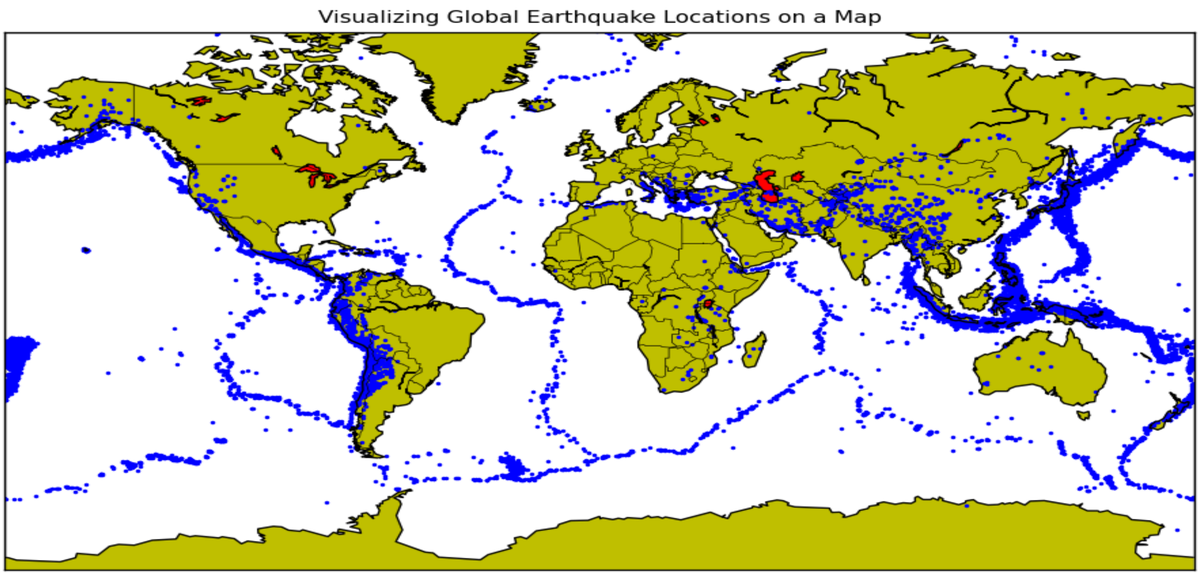

Figure (3) The Visualizing Global Earthquake Locations

3.4. The RNN and LSTM Model Architecture:

Multiple LSTM layers (1-3 layers) with 32-128 memory units , Dropout layers for preventing overfitting (0.2-0.5 rate),Dense layers for feature abstraction, Implementation using TensorFlow or PyTorch

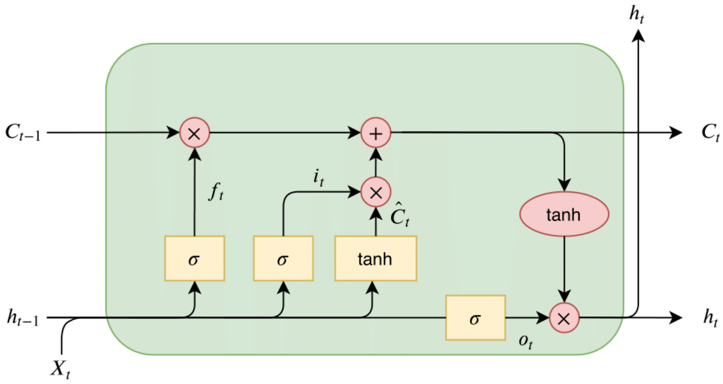

Figure (4) LSTM Architectures

3.5. The Model Training and The Optimization:

In this section we ,Implementation of Adam optimizer Mini-batch gradient descent , Learning rate tuning and gradient clipping , Activation functions: ReLU, Tanh, sigmoid Regular monitoring using validation metrics

Sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$ Range: (0, 1 Equation (1)

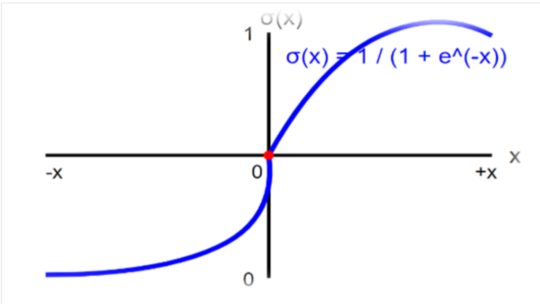

Figure (5) Sigmoid Activation Functions

The hyper tan

$$\mathbf{tanh(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$ Equation (2)

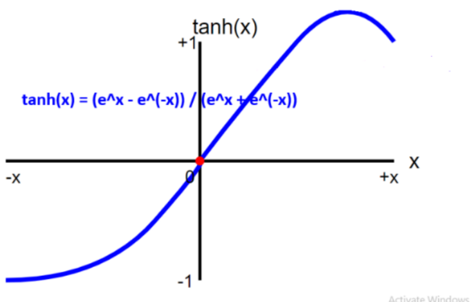

Figure (6) Tanh Activation Functions

ReLU (Rectified Linear Unit): Range: [0, ∞)

f(x) = max(0, x) Equation (3)

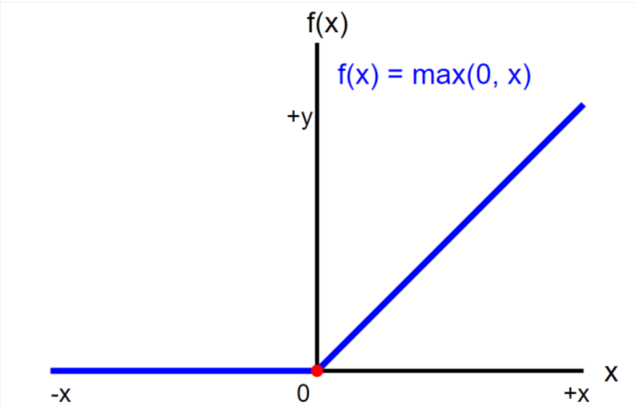

Figure (7) ReLU Activation Functions

3.6. The Model Evaluation and Deployment:

Performance assessment using test datasets the measures used are (MSE, RMSE, MAE) as well as find the value of (R2_score) Integration with IoT infrastructure - Real-time prediction system implementation,Alert mechanism development - Continuous monitoring and feedback loop establishment.

$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \ |yi{-}y^\wedge i|$ Equation (4)

$\text{M SE} = \frac{1}{\text{n}}\sum_{\text{i}=1}^{\text{n}}(yi - y^\wedge i)2$ Equation (5)

$RMSE{=}MSE$RMSE=MSE Equation (6)

$\text{R}^2 = 1 - \frac{\text{SSres}}{\text{SStot}}$ Equation (7)

3.7The methodology utilizes data from various sources, including:

3.7.1. U.S. Geological Survey (USGS)

3.7.2. European Mediterranean Seismological Center (ENSC)

3.7.3 Kaggle datasets containing real pre-recorded data

This comprehensive approach aims to create an effective earthquake prediction system by combining IoT sensor networks with advanced deep learning techniques, focusing on real-time monitoring and early warning capabilities.

4. The compation Result End Discassion

This study evaluates the efficiency of the proposed system explained in the previous study. It presents and discusses results. The behavior of the proposed system has been evaluated using a complete data set that contains Compare the use of activation functions (**Relu, tanh,Sigmoid**) with different optimization algorithms (**Adam , RMSprop, SGD).** Moreover, this chapter presents a detailed description and discussion of experimental results in each stage of the proposed system.

Table (1) Model summary of Lstm

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 4, 128)	68,096
dropout (Dropout)	(None, 4, 128)	0
lstm_1 (LSTM)	(None, 4, 64)	49,408

Dropout_1 (Dropout)	(None, 4, 64)	0
lstm_2 (LSTM)	(None, 32)	12,416
Dropout_2 (Dropout)	(None, 32)	0
dense (Dense)	(None, 16)	528
Dense_1 (Dense)	(None, 1)	17

The **Table (1)** Model summary of Lstm In this table we can see the number of layers used with the number of parameters for each layer with knowledge of the total parameters of the model (130,465)

4.1. DATASETS:

Research needs data, and only with numerous different types of data sets can one achieve a comprehensive understanding of the problem. data for the proposed system how to explain The Table of features of datasets: We used this data Tags tabular; Schemes and drawings datasets as follows. the **Table (1)** Features of datasets explanation of the data used.

4.2. Tabular Models:

Three models are used,(Model_1 , Model_2 , Model_3) each model contains three tests to find the best results in each model, in this section and can be explained as follows:

4.2.1. Model_1:

The ferset model, use (Relu) activation function was used with optimization algorithms (Adam , RMSprop, SGD) in order to find the best good model that can predict and the measures used are (MSE, RMSE, MAE) as well as find the value of (R2_score) ~~as shown in Table ( )~~, knowing that Learning Rate is equal to (0.001) and Epochs is equal to (200).

4.2.2. Model_2:

The second, model, use (tanh) activation function was used with optimization algorithms (Adam , RMSprop, SGD) in order to find the best good model that can predict and the measures used are (MSE, RMSE, MAE) as well as find the value of (R2_score)~~,~~ knowing that Learning Rate is equal to (0.001) and Epochs is equal to (200).

4.2.3. Model_3:

The third model, use (Sigmoid) activation function was used with optimization algorithms (Adam , RMSprop, SGD) in order to find the best good model that can predict and the measures used are (MSE, RMSE, MAE) as well as find the value of (R2_score) knowing that Learning Rate is equal to (0.001) and Epochs is equal to (200).

In the table (2) the results of the used models are presented, which gave the best results with the use of activation functions (Relu, tanh,Sigmoid) and optimization algorithm (adam).

Finaly the Comparison of the results Model_1 and Model_2 , Model_3 can be show Table (2) explaien

Table (2) Comparison of the results Model_1 and Model_2 , Model_3

Model	AF	OPT	MSE	RMSE	MAE	R2_score
Model_1	**Relu**	**adam**	**0.0003**	**0.0164**	**0.0145**	**0.9984**
Model_2	tanh	adam	0.0005	0.0241	0.0224	0.9966
Model_3	Sigmoid	adam	0.0025	0.0554	0.0447	0.9826

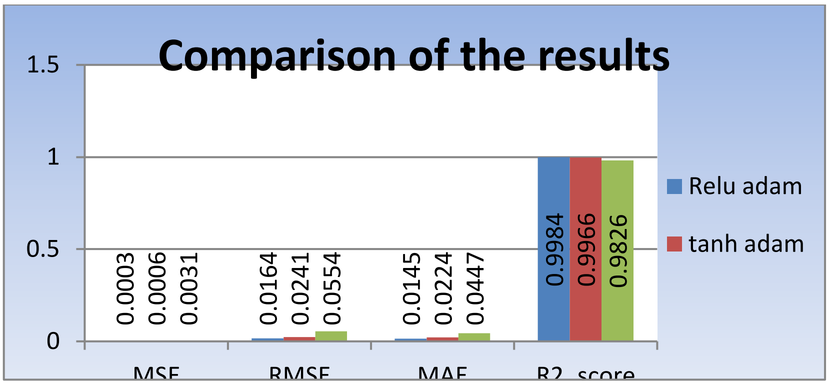

Figure (8) Comparison of the results _ Model_1& Model_2& Model_3

Table (3) Estimated Executing Time of Model_1 & Model_2& Model_3

Time of Model_1	Time of Model_2	Time of Model_3
2s 8ms/step	4s 17ms/step	3s 8ms/step

5.5 . Evaluate of Proposed System

At this stage, the proposed system was evaluated with data types with different performance metrics such as (MSE RMSE MAE R2_score) It is based on real data containing all data sources used in the recording and addressing of earthquakes, Where it has been tested on more than one model to reach the best results, the system can be evaluated .

5.5.1. Testing the Proposed System

Initially, the proposed system was applied to real data by making three models, each model contains three separate test cases, where Reliance was placed on the change of the type of activation functions with the change of optimization algorithms in each case of the model mentioned and explained in detail in this chapter, where different results were collected from the repeated inspection process and a certain decision was reached to choose the model and the best and best case represented by the following table (4).

Table (4) the best results

Model_1	AF	OPT	MSE	RMSE	MAE	R2_score
Case1	Relu	adam	0.0003	0.0164	0.0145	0.9984

In this table (4) the best results showing the optimal condition for obtaining the highest evaluation and the results obtained in this work from the proposed system activation function (Relu) and optimization algorithm (adam) were presented in the first model to obtain results **MSE**(0.0003) **RMSE**(0.0164) **MAE** (0.0145) **R2_score** (0.9984).

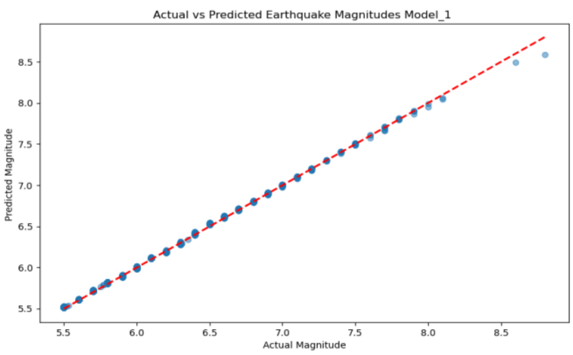

Figure (9) Actual vs Predicted Earthquake

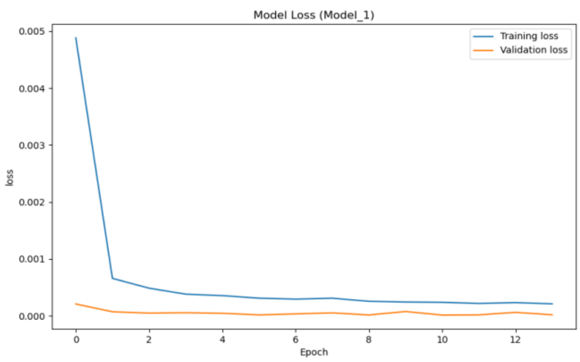

Figure (10) Model Loss (Model_1)

In summary, it seems to us that the proposed system is good, powerful and reliable to give high accuracy results obtained and can be applied with different data at various times and places ,Which indicates the possibility of applying this proposed system and relying on it to predict future earthquakes and its application in a wider field .

Conclusion

The main goal of the proposed system is to predict earthquakes by integrating IoT technology with artificial intelligence , Specifically, the use of deep learning, where Reliance was placed on building a data collection system by iot, as well as the data processing phase based on deep learning using the LSTM -RNN algorithm and building a model for predicting earthquakes based on activation functions (Relu, tanh,Sigmoid) and optimization algorithms (Adam , RMSprop, SGD) to reach the best results in the proposed system .

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