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# Machine Learning-Based Earthquake Prediction Technique Using Recurrent Neural Network Algorithm

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**ABSTRACT:** An earthquake is one of the most devastating natural catastrophes that may cause major infrastructure damage and casualties. Early earthquake detection can be crucial for minimizing damage and saving lives. Machine learning is a powerful tool that may be used to forecast earthquakes based on historical seismic data and other geographical data. This study is performed on par with the motivation of studying damage-causing natural disasters by predicting certain parameters of an earthquake. Artificial Neural Networks (ANN) have been used to train our model on a dataset containing many earthquake parameter fields. Therefore, earthquake prediction is a very necessary task. This study uses multiple RNN models to predict different information of an earthquake from multiple dimensions: including time information, latitude and longitude information, magnitude information, etc., and finally integrated them together, so as to avoid displaying only one dimension of earthquake information. It can show the earthquake situation more comprehensively. To predict the magnitude and depth of an earthquake at a particular latitude and longitude taking them as input. The proposed method using to earthquake prediction based predict the implementation of Recurrent Neural Network algorithm (RNN) using human behavior data sets and preprocess, classified of the prevention. Our model predicts the magnitude and depth of earthquakes at a given location with better accuracy. This advancement in seismology will help reduce huge damage and affect human lives. The accurate prediction leads to having more time to take precautionary measures before an earthquake hits. The paper shows the ability of models to predict the parameters of earthquakes accurately.

**KEYWORDS***:* Artificial Neural Networks (ANN), Recurrent Neural Network Algorithm (RNN), Machine Learning, Earthquake Prediction Technique.

## I. INTRODUCTION

Earthquakes are one of the most destructive natural disasters. They usually occur without warning and do not allow much time for people to react. Therefore, earthquakes can cause serious injuries and loss of life and destroy tremendous buildings and Earthquake is a natural catastrophe, which is occurred due to the impingement of tectonic plates. This leads to the release of a great amount of the earth's internal energy. These earthquake events normally occur in places, which are on the geographical fault lines and a great number of rocks move against each other. Liquid magma is stored in the core of the earth and it leads to a very high temperature resulting in massive energy. These energies require to be released and fault lines help them escape the core of the earth, which causes a great tremor. This vibration is recognized as an earth quake event. Earthquakes cause great damage to infrastructures, life and may even lead to another natural catastrophe called Despite the notable lack of success in reliably predicting destructive earthquakes, there has been a resurgence of research on earthquake predictability motivated by better monitoring networks and data on past events, new knowledge of the physics of earthquake ruptures, and a more comprehensive understanding of stress evolution and transfer.

However, the study of earthquake predictability has been hampered by the lack of an adequate infrastructure for conducting prospective prediction experiments under rigorous, controlled conditions and evaluating them using accepted criteria specified in advance. To address this problem, the working group on Regional Earthquake Likelihood Models (RELM), supported by the Southern California Earthquake Center (SCEC) and U. S. Geological Survey (USGS), has recently established a facility for prospective testing of scientific earthquake predictions in California, and a number of experiments are now underway and references therein. The RELM project conforms to the requirements for well-posed prediction experiments through a strict set of registration and testing standards. Infrastructure, leading to great economy loss. The prediction of earthquakes is obviously critical to the safety of our society, but it has been

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proven to be a very challenging issue in seismology. With the development of data mining techniques, a large number of scholars have devoted to discover the earthquake patterns from seismic time series based on various feature extraction methods and achieved some success. Since designed seismic indicators based on mathematical statistical methods, e.g. earthquake magnitude, earthquake energy, earthquake acceleration, and value and so on, a lot of researchers have proposed different feature extraction methods to obtain indicators for earthquake prediction. One category is based on the fixed number of seismic events. For example, applied the sliding time and space windows containing a fixed number of seismic events to obtain earthquake indicators. Based on this method considered a fixed number of seismic events before main earthquake as the precursory pattern to extract features, which is useful for analyzing the trend of earthquakes.

## II. LITRATURE SURVEY

Existing works on earthquake prediction can be mainly classified into four categories according to the employed methodologies mathematical analysis precursor signal investigation machine learning algorithms like decision trees and support vector machines (SVM), and deep learning. The first type of work tries to formulate the earthquake prediction problem by using different mathematical tools like the FDL (Fibonacci, Dual and Lucas) method, kinds of probability distribution or other mathematics proving and spatial connection theory. In the second type of work, researchers study earthquake precursor signals to help with earthquake prediction. For example, electromagnetic signals, aerosol optical depth (AOD), lithosphere-atmosphere ionosphere and cloud image have been explored. Even animals' abnormal behavior has been taken into account in this kind of study. And artificial neural networks (ANNs) to predict the magnitude of the largest earthquake in the next year based on the previously recorded seismic events in the same region. Earthquake is one of the devastating events in natural hazards that causes great casualties and property damage every day in the world since that it is hard to predict. With the increasing amount of earthquake datasets collected, many researchers try to solve the task of predicting the earthquake in the future time [1-4].

Earthquake prediction is to estimate the time, location and magnitude of the future earthquake, which is one of the theoretical foundation of geophysics, geology, computer science. However, this feature extraction method cannot detect the range of earthquake magnitude of main shock well. The work in, similarly, extracted features from the fixed length seismic sequences before main earthquake, which can estimate the magnitude of earthquakes. However, the methods mentioned above cannot infer the effective time range of earthquake prediction results. Thus, another feature extraction method based on the fixed length of time before main shock is proposed to make earthquake prediction. Specifically, the historical earthquake records for a given region are divided into a number of pre-defined equal time periods such as one month or 15 days in. The advantage of this method is that the representative training samples can be obtained, which is critical for the learning of earthquake prediction models. But the fixed time window cannot make full use of the events before the main shock in current time period and lead to unsatisfactory prediction results [5-8].

To this end, in this paper, we propose a precursory pattern based feature extraction method for earthquake prediction, which can predict both the magnitude range of future earthquakes and obtain the effective time range of prediction results. In this study, earthquake precursor refers to a part of seismic records before the main shock, which is represented as the precursory pattern of earthquake. In order to obtain the representative learning samples, the raw seismic data is firstly divided into a set of fixed day time periods and the magnitude of the largest earthquake of each time period called main shock is as the label of the fixed period. An earthquake emergency command system is designed based on cloud computing and the Internet of Things (IoT) to mitigate slow information acquisition, low processing efficiency, and weak information storage and communication ability in earthquake rescue [9-12].

Subsequently, a new earthquake emergency command system is built based on cloud computing and IoT technology along with data from satellite mid wave infrared remote sensing. Finally, system feasibility is evaluated. The results show that surface radiation changes significantly before an earthquake; infrared brightness and temperature fluctuates drastically; and the abnormal region gradually approaches the epicenter of the earthquake. The peak value of the relative power spectrum in the earthquake is more than 9 times the average. In conclusion, the proposed emergency command system based on satellite remote sensing data, cloud computing, and IoT can yield good evaluation results demonstrating that multidimensional satellite thermal infrared remote sensing data analysis can improve the accuracy of earthquake prediction. Earthquake prediction is an important and complex task in the real world. Although many data mining-based methods have been proposed to solve this problem, the prediction accuracy is still far from satisfactory due to the deficiency of feature extraction techniques [13-16].

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To this end, in this paper, we propose a precursory pattern-based feature extraction method to enhance the performance of earthquake prediction. Especially, the raw seismic data is firstly divided into fixed day time periods, and the magnitude of the largest earthquake in each fixed time period is labeled as the main shock. The precursory pattern is a part of the seismic sequence before the main shock, on which the existing mathematical statistic features can be directly generated as seismic indicators. First, cloud computing technology is introduced, and a traditional earthquake emergency command system is analyzed comprehensively. Then, the characteristics of mid wave infrared remote sensing data are explored before and after recent earthquakes based on satellite remote sensing data. Based on these precursory pattern-based features, a simple yet effective classification and regression tree algorithm is adopted to predict the label of the main shock in a pre-defined future time period [17-20].

## III. IMPLEMENTATION OF PROPOSED METHODOLOGY

In this section we have to discuss the various process of predicting the earthquake prediction cases. First we collect dataset and then preprocess the collected dataset, after that we have to extract the features from the dataset and select the best valuable features and finally the features can be classified by using RNN algorithm.

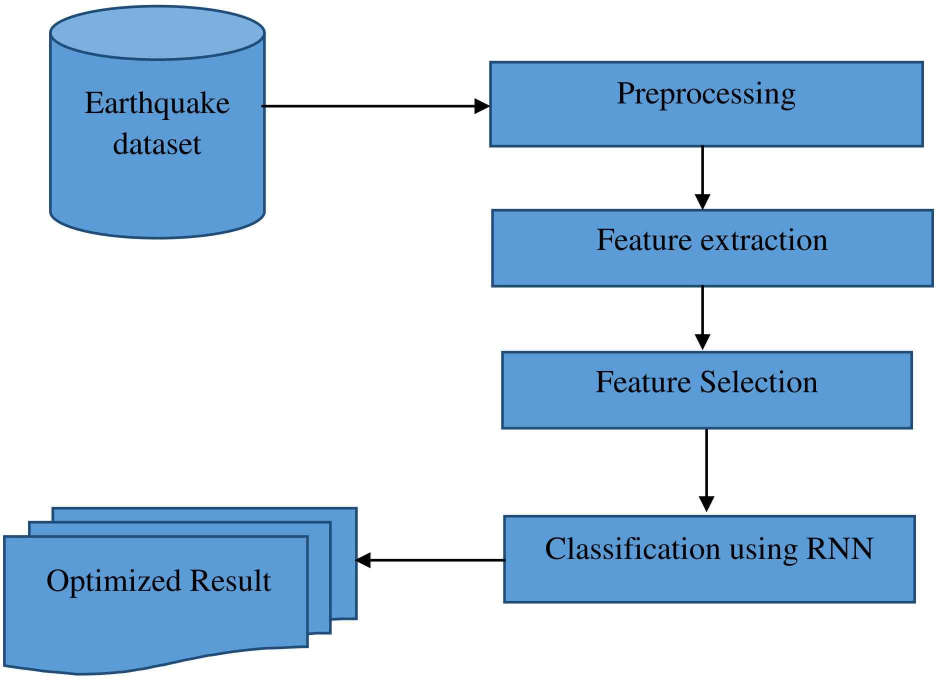


Figure 1.1 Basic flow diagram of earthquake prediction

Figure 1 described as. Earthquake prediction detection is processed in different stages such as pre-processing, feature extraction, feature selection and classification. Generally, there are four phases to determining whether or not you have earthquake prediction. The first phase entails obtaining earthquake prediction dataset. In the second phase, data set can be pre-processing to improve the quality. In the third phase, data extraction can extract the best feature in the trained dataset. Data segmentation is the fourth phase, and finally the data set can be classified and obtained the result.

### 3.1 dataset collection

This is a compiled dataset pulled from four other datasets linked by time and place from year 1985 to 2016. The source of those datasets is WHO, World Bank, UNDP and a dataset published in Kaggle. The overview of this dataset is, it has 27820 samples with 12 features. Download the dataset from the link provided.

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### 3.2 Preprocessing

Data preprocessing is a critical step in the artificial intelligence process. Analysis of data without careful consideration can yield misleading results. For this reason, the representativeness and quality of the data should first be ensured before conducting the experiment. Preprocessing tasks include data cleaning such as identification and outlier removal, data integration, data transformation generating new features, and data reduction. The deliverable of the data preprocessing task is a new training set that ultimately leads to improved classification performance and reduced classification time. This is due to the reduced dimensionality of the data, which allows the learning algorithm to work faster and more efficiently. In some cases, it can increase the accuracy of future classifications. For others, the result is a more compact and interpretable representation of the target concept.

### 3.3 Feature Extraction

Tweets expressing earthquake thoughts do not have a pre-defined semi-fixed lexical-syntactic pattern. Therefore, it requires the use of hand engineering and analysis of a set of features, rather than embedding sentences or words in a supervised setting using deep learning models such as convolution neural networks (CNNs). The proposed method makes use of the following set of features for classification. An RNN implementation of a tree-structured approach to extracting phrase semantics has been used for text classification with promising results in previous studies. However, the developed model suffers from the problem of gradient vanishing and exploding, so it takes a long time to develop a text tree structure for handling long tweets. Two forms of RNN-based design approaches have been created: LSTM and GRU. Both contain gating mechanisms that handle the limitations of RNNs. It incorporates "forget" gates that allow the network to encapsulate long-term relations without encountering the vanishing gradient problem.

```
Algorithm:
Begin
        Initialize the features population
        Calculate the feature fitness and weights
                Select global and local leader
        While (termination criteria is not satisfied) do
                Updated the position of spider based female (Sf)
                Updated the position of spider based male cooperative operators (Mf)
Perform matting processing
        Termination criteria
                Ite=iter + 1
End
Optimization solution
Stop
```

### 3.4 feature selection

In the process of machine learning model development, only a few variables in the data set are useful for model construction, and the remaining features are redundant or irrelevant. Inputting a dataset with all these redundant and irrelevant features can negatively impact and degrade the overall performance and accuracy of the model. Therefore, it is very important to identify and select the most relevant features from the data, and to remove irrelevant or less important features by using machine learning feature selection.

```
Algorithm
start
feature_name = X.columns.tolist()
# calculate the correlation with y for each feature
        for i in X.columns.tolist():
         cor = np.corrcoef(X[i], y)[0, 1]
          cor_list.append(cor)
end
  # replace NaN with 0
          cor_list = [0 if np.isnan(i) else i for i in cor_list]
# feature name
         cor_feature = X.iloc[:,np.argsort(np.abs(cor_list))[-num_feats:]].columns.tolist()
 # feature selection? 0 for not select, 1 for select
        cor_support = [True if i in cor_feature else False for i in feature_name]
        return cor_support, cor_feature
```

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```
        cor_support, cor_feature = cor_selector(X, y,num_feats)
        print(str(len(cor_feature)), 'selected features')
stop
```

### 3.5 Classification using RNN

The classification method is used to classify the best feature to predict the earthquake prediction case.RNNs generate feature classifications by convolving different sub regions of a dataset with pre-trained kernels. In addition, nonlinear activation functions such as sigmoid, tanh, and linear correction functions can be applied. This method of reducing the amount of calculation is a data set, in which a feature region is selected, and the largest value in it is selected as a representative. It is used with a traditional fully-connected RNN and is usually used in the output stage.

Algorithm

Step 1: Initialization of the dataset

Step 2: To collect the dataset

Step3: Then, dataset are pre-processed

Step 4: The dataset under cleaning and data reduction process by using feature extraction.

Step 5: The trained features are selected by feature selection process.

Step 6: The proposed algorithm Recurrent Neural Network (RNN)is evaluatedearthquake prediction prediction performance.

Step 5: finally produce the optimized result.

The generalized neural network different layers are represented as follows:

$$E[y|\boldsymbol{x}] = \frac{\int_{-\infty}^{\infty} y \cdot f(\boldsymbol{x}, y) \cdot \mathrm{d}y}{\int_{-\infty}^{\infty} f(\boldsymbol{x}, y) \cdot \mathrm{d}y}$$

## IV. RESULT AND DISCUSSION

The proposed system Recurrent Neural Network (RNN) for data processing is implemented for detecting earthquake prediction. Earthquake prediction includes dataset, preprocessing, feature extraction, feature selection and classification. This describes a method for detecting the earthquake prediction case the algorithmis described for the detection of earthquake prediction.

**Table 1: dataset Accuracy Performance**

| No. of data | SVM % | CNN % | RNN% |
|---|---|---|---|
| 1 | 46 | 53 | 69 |
| 2 | 56 | 65 | 75 |
| 3 | 63 | 70 | 81 |
| 4 | 65 | 73 | 88 |
| 5 | 76 | 88 | 93 |

Table 1 shows the analysis of accuracy level performance on the proposed algorithm RNN comparing with other algorithm.

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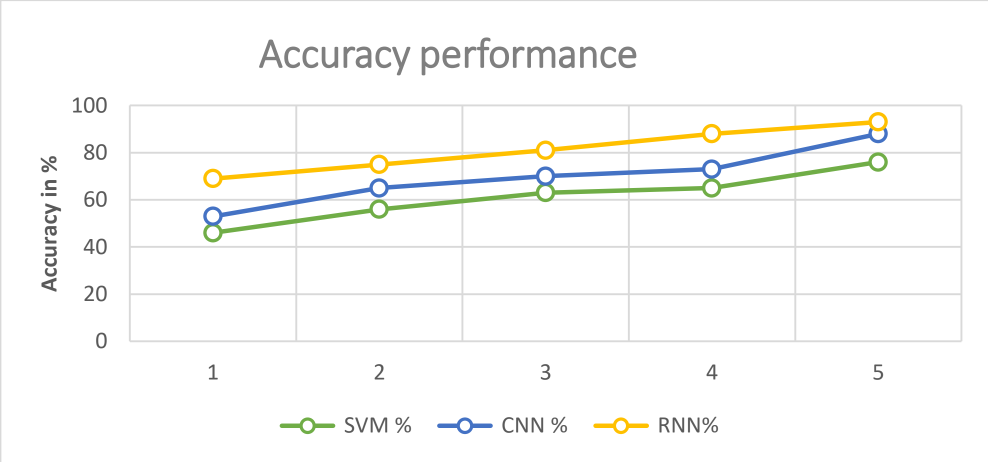


**Figure 5: Analysis of accuracy performance**

Figure 5 shows the analysis of accuracy performance in the proposed algorithm RNN. The existing system Support Vector Machine (SVM) provides 76 %, and CNN 88 %, and then, the proposed algorithm RNN provides 93% accuracy performance.

**Table 2: Analysis ofPrediction performance**

| No. of Data | SVM % | CNN % | RNN% |
|---|---|---|---|
| 1 | 47 | 61 | 66 |
| 2 | 57 | 65 | 75 |
| 3 | 65 | 73 | 80 |
| 4 | 72 | 80 | 85 |
| 5 | 79 | 88 | 90 |

Table 2 shows the analysis of prediction level performance on the proposed algorithm RNN comparing with other algorithm.

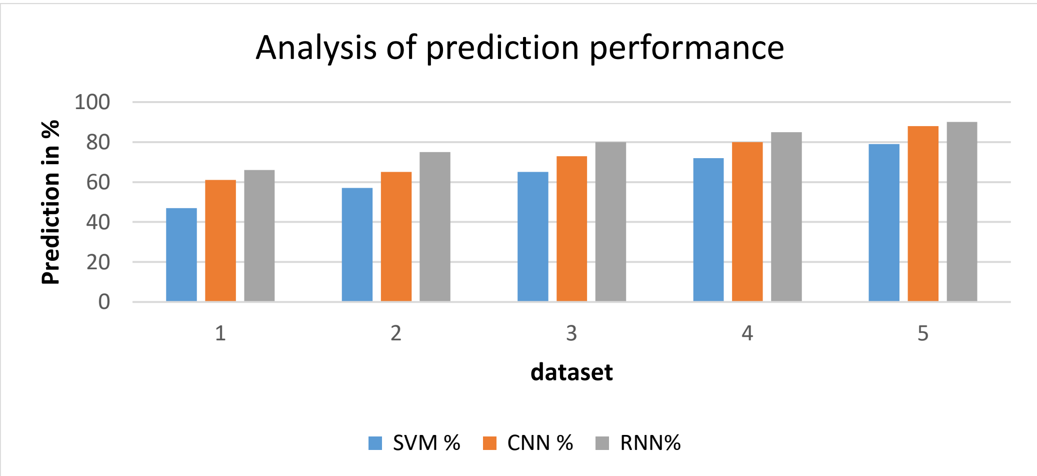


**Figure 6: Analysis of prediction performance**

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Figure 6 shows the analysis of prediction level performance in the proposed algorithm RNN. The existing system Support Vector Machine (SVM) provides 79 %, and CNN provides 88%, and then the proposed algorithm RNN provides the prediction performance of 90%.

**Table 3: Analysis of time complexity performance**

| No. of data | SVM % | CNN % | RNN% |
|---|---|---|---|
| 1 | 55 | 50 | 47 |
| 2 | 50 | 49 | 42 |
| 3 | 48 | 45 | 40 |
| 4 | 44 | 40 | 39 |
| 5 | 39 | 35 | 33 |

Table 3 shows the analysis of time complexity level performance of the proposed algorithm RNN comparing with other algorithm.

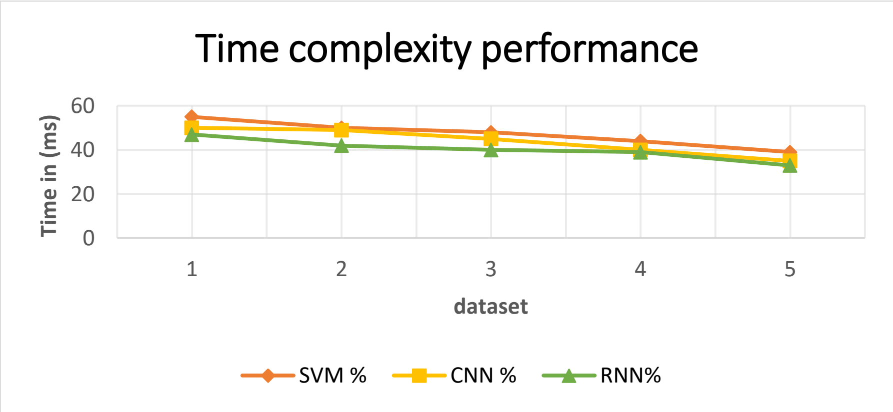


**Figure 7: Analysis of Time complexity**

Figure 7 shows the analysis of time complexity performance of the proposed algorithm RNN. The existing system Support Vector Machine (SVM) produces 39 ms, and CNN produces 35 ms, and then, the proposed algorithm RNN produces lowest time performance of 33 ms.

## V. CONCLUSION

An evaluate the performance of the proposed approach on earthquake datasets from different regions and demonstrate its high accuracy in earthquake prediction. Our study provides a new perspective on earthquake prediction using machine learning techniques and highlights the potential of deep learning approaches for improving earthquake prediction. The proposed approach uses a convolutional neural network to extract relevant features from the seismic data, and a long short-term memory network to predict the probability of an earthquake. The proposed approach can be used in conjunction with existing earthquake prediction methods to provide more accurate and reliable predictions, which can help mitigate the potential impact of earthquakes on human life and infrastructure. The study introduces the process of preprocessing, modelling, evaluation, and visualization of disaster data. An earthquake disaster inversion model based on traffic data has been established, which can predict the earthquake intensity based on the relevant data provided by the traffic department. The prediction accuracy is relatively accurate, which is very helpful for earthquake prediction and rescue operations.

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