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Comparative Analysis of Machine Learning Models for Earthquake Prediction: Evaluating LSTM and Logistic Regression Using Seismic and Metadata Features

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ABSTRACT

Being able to predict an earthquake in advance ensures that meaningful steps are taken to mitigate a disaster and manage its impacts on human life and infrastructure. The aim of this research is to utilize machine learning algorithms to fully automate the detection of early signs of a potential earthquake using real-time streaming data for seismic analysis. The study compares the performance of modern deep learning techniques (LSTM, CNN) with that of older, more established statistical techniques like Logistic regression, KNN, and Decision trees for the prediction of seismic activities. Unlike the traditional method which relies only on primary wave signals as the sole input, it integrates associated earthquake metadata to enhance forecast precision and expedite alarm issuance. Also included in this work is an automated alert system that has the capability to autonomously and instantly generate messages and dispatch them through a specified communication port, thereby guaranteeing that sensitive populations are alerted in a timely and effective manner. The experiments illustrate that machine learning techniques are capable of accurately detecting the signatures of seismic activity and providing prompt reliable warnings. This research also highlights the importance of integrating artificial intelligence-based prediction models to disaster management systems to improve the level of response to emergencies. The emerging data-driven systems for issuing early warning alerts can enhance earthquake prediction and disaster management, thus improving the current position of technology. This research proves its feasibility.

1. Introduction

Earthquakes are one of the most destructive natural disasters, causing huge damage, many deaths and severe economic impacts. Early warning systems (EWS), which can signal the onset of harmful seismic activity before it starts, are essential to reduce these impacts. To warn of the arrival of more destructive secondary waves (S- waves), traditional EWSs have relied primarily on detecting seismic waves, particularly primary waves (P- waves)[1]. However, these methods are limited by the speed of detection, the availability of seismic infrastructure, and the inability to forecast earthquakes over longer periods[2]. Furthermore, not all regions have the expertise and large sensor networks required for current early warning systems, particularly in low-income countries with limited resources for seismic monitoring[3]. With the advancement of machine learning, predictive modelling has emerged as a new technique to improve earthquake forecasting[2]. Long Short-Term Memory (LSTM) networks and other deep learning techniques have shown potential in analyzing seismic waveforms to detect pre- earthquake patterns[4]. These models help to derive complex patterns from unprocessed waveforms because they can identify long-term dependencies in continuous seismic data[5].

Although LSTM models have been shown to have strong predictive capabilities, their feasibility in real time applications is limited by their high interpretation requirements, long training cycles, and dependence on large amounts of sequence data[6]. In addition, the adoption of such models in the real world becomes even more difficult due to the need for large labelled datasets and continuous retraining, especially in regions where access to advanced computing devices is difficult[7]. In contrast to LSTM, this study explores the possibility of metadata- driven machine learning techniques (especially logistic regression) for earthquake prediction. Unlike deep learning algorithms that process raw seismic waveforms, logistic regression uses organized seismic metadata that contains factors such as magnitude, depth, location and historical seismic trends[10]. By focusing on statistically relevant seismic metrics rather than complex time-series processing, metadata-based techniques have the potential to speed up predictions and reduce resource consumption[11]. The approach aims to provide a deployable and computationally efficient solution for real-time earthquake prediction by utilizing metadata rather than waveform analysis[10]. To determine the best machine learning strategy, this study evaluated the K-Nearest Neighbors (KNN) decision tree and CNN models, as well as logistic regression[12]. The best-performing models were incorporated into a FastAPI-based system that uses the Meta Cloud API to distribute real-time earthquake alerts via WhatsApp[16]. This ensures that alerts are fast and accessible, and reach affected populations quickly through increasingly ubiquitous communication channels, thus improving disaster preparedness and response strategies[17]. The main objective of this study is to determine whether LSTM models trained on seismic waveforms perform better than Logistic regression trained on seismic metadata[5].It also examines the computational efficiency, recall, accuracy, and precision of earthquake prediction models such as decision trees, KNNs, and logistic regression[13].

Along with implementing FastAPI and WhatsApp, the most effective machine learning models will also be incorporated to formulate an advanced real-time seismic alarming system[16].This study aims to determine if machine learning models driven by metadata could effectively replace the need for real-time notification systems for earthquakes by minimizing the need for crucial waveform data and computational resources[11].This research will determine if metadata-driven models can accurately predict earthquakes by using various models and evaluating their performance against and for providing effective and accurate prediction. The central assumption of the study is that logistic regression achieves a comparable to equal level of predictions in comparison to LSTM models, but does so more efficiently when using structured seismic metadata prompting more suited computations for real-time applications[10].In computationally weak but seismically active regions, important metadata patterns can rapidly be extracted through logistic regression while LSTM models are burdened with constant waveform scrutiny along with comprehensive preprocessing[7]. This study aims to enhance the realm of disaster management by creating an accurate, efficient, and lightweight real-time earthquake prediction model based on metadata-driven predictive modeling[11]. The outcomes of this study can help in optimizing some mechanisms of disaster preparedness, improving public safety, and strengthening the existing early-warning systems[3].

2. Literature Review

Machine learning has transformed earthquake prediction by enabling researchers to discover complex patterns from large-scale seismic datasets[2]. Statistical techniques and geophysical metrics (e.g., fault line stress accumulation, historical seismicity, and tectonic plate motion) have long been the backbone of traditional earthquake prediction models[4].However, these traditional methods tend to be poorly generalized and inaccurate and are unable to adapt to the ever-changing seismic situation[5].To improve real-time prediction capabilities and forecast accuracy, researchers have adopted sophisticated machine-learning methods. Deep learning methods, particularly Long Short-Term Memory (LSTM) networks, are among the most widely studied machine learning models for earthquake prediction. LSTM has proven to be very successful in identifying long-term relationships in continuous seismic data by analyzing seismic waveform patterns over time[7].These networks are ideal for time-series-based earthquake forecasting because they can store data from previous occurrences. It has been shown that LSTM models can successfully detect earthquake precursors by analyzing P-wave signals, tremor activity and other seismic changes[8].However, despite its great potential, LSTM has significant drawbacks. Since LSTM relies on a large amount of annotated seismic waveform data, it requires a large dataset, powerful computational capabilities, and a long training cycle, resulting in high computational costs[6].In addition, when trained on small datasets, LSTM is prone to overfitting, which limits its ability to make inferential predictions for earthquakes that have not yet occurred[7].These difficulties limit the application of LSTM models in real-time earthquake early warning systems (EEWS), especially when processing infrastructure and resources are limited[6].
To deal with these issues, researchers have been looking for other methods of machine learning that might enhance real-time functionality and minimize costs simultaneously. Logistic regression (LR) is a statistical method of classification that operates on structured data instead of raw data such as seismic waveforms[10].So, it is convenient to use logistic regression in the prediction of earthquakes because of its great simplicity, ability to be interpreted, and computational effectiveness[11].Even though deep learning approaches require a long and detailed treatment of time-series data, earthquake size, depth, location, historical seismic activity, and regional tectonic information are all used in constructing the seismic contours in logistic regression[10].Since LR focuses on these structured features, it is very accurate and does not require sophisticated pre-processing.

Also, this study allows for the further examination of the new hybrid strategy incorporating constrained seismic waveform analysis and metadata-based prediction that can potentially improve the overall effectiveness and precision of forecasting systems, which is the goal of this research[3].This approach was designed to help solve the shortcomings of current earthquake prediction methods and vastly mitigate the impact of seismic hazards globally[1].This metadata methodology not only enables effortless real-time predictions, but greatly enhances the practicality of widespread implementation[3].
Though logistic regression is (LR) a lightweight predictive model, there is a need to investigate other techniques of machine learning ranging from convolutional neural networks (CNN), K-nearest neighbors (KNN), decision trees, and others[5]. Despite the fact that convolutional neural networks are mostly applied to tasks of object recognition and

some lower- level spatial features, they have been intimidated to analyze seismic data. CNNs utilize geographic patterns and the relationships among earthquakes to process seismic data. CNNs can recognize patterns in space but are not as efficient as traditional metadata-based models for real-time applications because of the excessive amount of training data and computational power needed[8].On the other side of the KNN spectrum, a non- parametric algorithm that classifies objects by considering their neighbors, KNN provides an intuitive classification framework for predicting earthquakes by analyzing seismic data and finding similar antecedent seismic activities[10].Whereas KNN provides an intuitive framework, it has the downside of having to keep track of and compare each sample to provide a resultant class for a given sample, which becomes quite costly in terms of computation time for larger datasets, thereby decreasing responsiveness and scalability rendering it useless in real-time prediction systems. In contrast, Decision trees are fast and easy to understand, and also effective in capturing non-linear patterns in seismic data. They are, however, extremely prone to overfitting particularly when trained on small or very noisy datasets[10].Due to the presence of overfitting, the adaptability of predictions is lowered and in real-world seismic environments, the prediction performance variation is negated[12].

Notwithstanding the existing models presented above, metadata-driven techniques emerged as the most feasible brute force method to apply deep learning in seismic forecasting due to the tremendous deficits of each of the presented models[3].Metadata based deep learning models were less efficient waveform based models in terms of time and resource consumption in reading, training, and computing[2].This work combines CNN with KNN, decision trees, and logistic regression to determine what combination yields the highest accuracy, efficiency, and performance under stringent time constraints[10].Furthermore, we take a step further on model performance evaluation by integrating the best model into a real-time earthquake alert system. The implemented model is capable of notifying users through WhatsApp (Meta Cloud API) and FastAPI of any seismic activity in real-time. This was done in order to use technology in minimizing the gap between prepared and actual emergency response, which can enhance disaster readiness, especially during critical situations[16].

This work seeks to aid in the production of scalable, functional and deployable earthquake prediction systems through systematic assessment of deep learning and metadata-based machine learning models. The results of this project will lay the groundwork for new approaches to predictive analytics within the field of earthquake forecasting and lightweight machine learning models can be efficiently used for real-time disaster response[4].

3. Problem Statement

Earthquakes wait individual of the most trenchant unaffected disasters, generating huge death, infrastructure damage, and financial disruptions [1]. Early warning orders (EWS) play a crucial duty in diminishing these impacts by providing up-to-date alerts before major tectonic occurrences occur [3]. Traditional upheaval forecast models rely laboriously on basaltic waveform study, with deep knowledge approaches to a degree Long Short-Term Memory (LSTM) networks being widely used to recognize patterns in constant tectonic data [6]. While LSTM models have displayed powerful predictive facilities, their proficient arrangement in real-opportunity schemes faces several challenges [7]. These contain extreme computational complicatedness, long training phases, reliance on large marked datasets, and the necessity for leading processing foundation [8]. As a result, their practicability is significantly restricted, specifically in earthquake-likely domains accompanying scarce computational possessions [6].

Given these disadvantages, this research investigates whether metadata-compelled machine intelligence models, specifically logistic regression, can present image of a reasonable alternative to LSTM-based tectonic predicting [10]. Unlike LSTM, that requires far-reaching waveform study, logistic regression and different metadata-located models influence structured tectonic attributes in the way that magnitude, wisdom, area, and ancient seismic flows to think earthquakes [11]. These models offer benefits in agreements of computational efficiency, ease of arrangement, and diminished confidence on large-scale basaltic waveform datasets [10]. However, their predicting accuracy and dependability distinguished to deep knowledge methods wait changeable [5].

This study aims to address two key research questions:

(1) Can logistic regression utilizing basaltic metadata obtain predictive conduct corresponding to or superior to LSTM models prepared on inexperienced basaltic waveforms? [10]

(2) How accurately can miscellaneous machine intelligence models—including decision seedlings, K-Nearest Neighbors (KNN), and convolutional affecting animate nerve organs networks (CNN)—call earthquakes, and what determinants influence their depiction? [6]

To answer these questions, the research evaluates and compares multiple machine intelligence approaches established their precision, recall, veracity, and computational adeptness [13]. The most active model is then joined into a certain-time temblor alert arrangement utilizing FastAPI and WhatsApp (via the Meta Cloud API) to give breakneck notifications to at-risk communities [16]. By investigating the practicability of metadata-driven machine intelligence models for basaltic prediction, this study aims to specify a climbable and adept alternative to waveform-dependent orders, embellishing disaster readiness and reaction in capability-limited domains [3].

4. Methodology

4.1 Dataset Used

The dataset employed in this research was accessed from the United States Geological Survey (USGS) earthquake catalogue. The dataset hold historical records of earthquakes with different seismic event attributes [2].The main attributes are:

- Magnitude (mag): The magnitude of the earthquake event.
- Depth (km): The depth of the event occurrence.
- Latitude and Longitude: The geographic location of the event.
- Time: Timestamp of the event occurrence.
- Tectonic Plate Data: The area where the earthquake happened.
- Regional Seismicity: Historical occurrences of earthquakes in the area.

The dataset offers a complete foundation for training machine learning models through the combination of seismic data with metadata to achieve high prediction accuracy [4].

4.2 Data Pre-Processing

Before using machine learning models, the dataset was cleaned to ensure quality and accuracy. To improve the effectiveness of algorithms, the data set needed cleansing. The procedures that were carried out include:

- Replacing Missing Values: Unattended missing data points could have a negative impact on the model. The following methods were utilized:
    - Missing Value for Numerical Features: For features such as depth and magnitude, missing values were replaced by median imputation.

- Missing Value for Categorical Features: Categorical missing values were substituted with the mode [5].

- Detection and Removal of Outliers: Model learning can be disturbed by outlier values. The Interquartile Range (IQR) method was applied, which extracts the first quantile of the value range to the last quantile of the value range [8]:

$$IQR = Q3 - Q1 \qquad \text{Lower Bound} = Q1 - 1.5 \times IQR$$
$$\text{Upper Bound} = Q3 + 1.5 \times IQR$$

Equation 1

Values outside this range were considered outliers and removed.

- Normalization and Scaling: To ensure each feature contributes equally, Standardization was applied with[6]:

$$Z = X - \frac{\mu}{\sigma}$$

Equation 2

4.3 Feature Engineering Enhancements

Feature engineering is essential to derive valuable information from crude seismic data and metadata. The objective of feature engineering for the case of earthquake prediction is to create features that represent both the physically measurable components of seismic events and historical data.

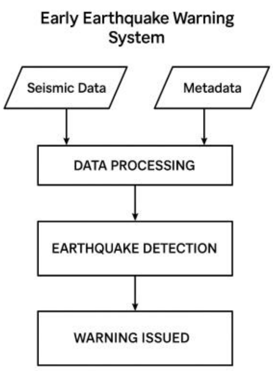

Fig.1. Flowchart

1. **Seismic Energy Estimation**
   With the use of the Gutenberg-Richter Law, the data is supplemented with an energy-based estimation of every earthquake's value [7].
2. **Tectonic Plate Dynamics**
   Instead of treating tectonic plate information as categorical features, it is converted into numerical features via one-hot encoding and geological stress measurement [3]. Another feature is the distance of an event to the plate boundaries.
3. **SpatioTemporal Clustering**
   DBSCAN algorithm is used to discover high-density seismically active areas. These clusters are used as another input for classification models to distinguish

between active and stable seismic zones [10].

4. **Recurrence Intervals & Historical Activity**
   Through the study of past earthquake events in an area, a feature for average recurrence time is added [9]. This enables models to model periodic seismic activity in active fault zones.
5. **Waveform-Derived Features (for Deep Learning Models)**
   Seismic waveforms can be converted into spectrograms or input into CNNs to derive frequency-based seismic signatures, which are helpful in identifying foreshocks from main shocks [13].

4.4 Model Selection & Training

Logistic Regression

Logistic regression gives a probability estimate of the earthquake based on the seismic data history [2]. Logistic regression assigns weights to all the features (temporal patterns, local seismicity, depth, and magnitude) to model their influence on the probability of the earthquake [5]. The model outputs a probability score, which a threshold (for example, 0.5) will determine whether there is an earthquake that will, or will not, happen [7]. The timestamps allow the model to recognize periodic seismic patterns, for example, seasonal and aftershock sequences [14]. Logistic regression assigns weights to these features and uses the sigmoid function to output a probability score [8]:

$$\sigma(z) = \frac{1}{1} + e^{\{-z\}}$$

Equation 3

where P(Y=1)P(Y=1)P(Y=1) is the chance or probability of experiencing an earthquake and the β values are required because they measure the degree to which each of the features contributes to the output [10]. The model considers several time-related features, including seasonal variations and aftershock sequences, to differentiate and determine probabilistic patterns with regard to the occurrences of earthquakes [16].

Decision Tree Classifier

Decision trees work by repeatedly and systematically splitting the data into subsets of diminishing size based on particular attributes, though not limited to, magnitude and depth [4]. Enhancing the process of recursive division is the aim of the ensuing information gain at each step [6]. As the model is processing data, it finds and creates a hierarchical set of decision rules that is encapsulated by the condition, "If magnitude is greater than X and depth is less than Y, then there is a possibility an earthquake will occur" [13]. Essentially, a decision tree classifies instances of earthquakes by continually making recursive divisions of data, which depend on attributes of magnitude and depth [11]. Each such division is optimized to produce the maximum amount of information gain, which is measured through the notion of entropy [9]:

$$Entropy = -\sum p(i) log_{\{2\}p(i)}$$

Equation 4

where p(i) is the probability that a point is of a given class [7]. The model produces a tree where each node is a decision based on attributes (e.g., "If magnitude > 5.0 and depth < 10 km, then classify as earthquake") [3]. Time-related attributes enable the tree to distinguish between single earthquakes and sequences (foreshocks, aftershocks) [15].

K-Nearest Neighbors (KNN)

KNN allocates a new seismic event according to its proximity to past earthquake records

[2]. It calculates the straight-line distance between feature vectors (time, depth, location, and magnitude) to determine the K nearest past events and allocates the most frequent label [10]. The time axis allows KNN to identify patterns of events happening before a major earthquake and thus is effective in aftershock prediction [5]. But it needs a proper dataset to predict accurately based on proximity [3]. The model calculates the straight-line distance between the event feature vector x and past earthquakes:

$$d = \sqrt{\{(x_2 - x_1)^2 + (y_2 - y_1)^2\}}$$

Equation 5

where x and y are feature vectors representing earthquake characteristics [7]. The model identifies K closest events and assigns the most frequent class [9]. Since earthquakes often occur in clusters, temporal features help KNN recognize patterns in seismic sequences [11].

Convolutional Neural Networks (CNN)

CNN is especially helpful if there is available seismic waveform data [2]. It learns spatial patterns from seismographic signals, extracting localized features like wave frequency, amplitude, and spectral properties that portend an impending earthquake [4]. CNNs are able to identify patterns related to various tectonic activities, allowing for high-resolution interpretation of seismic signals [9].

A convolutional layer uses filters to identify wave frequency and amplitude changes:

$$Z_{ij} = \Sigma_m \Sigma_n X_{(i+m)(j+n)} \cdot W_{mn}$$

Equation 6

where X represents the input seismic waveform, W is the filter matrix, and Zij is the feature map output [6]. By detecting unique signal signatures associated with different tectonic activities, CNN helps in recognizing micro-seismic precursors to larger earthquakes [14].

Long Short-Term Memory (LSTM) Networks

LSTM, a type of recurrent neural network (RNN), is best suited to analyze the temporal sequence of seismic data [3]. It has the ability to remember past seismic occurrences, and hence it can identify long-term earthquake dependencies [7]. The model considers trends such as earthquake swarms, large quake foreshocks, and cycles of seismic activity using timestamp data [9]. With its ability to learn from past experiences, LSTM can extract relationships between historical data and future events to make predictive estimates [4]. They have memory in cell states and refresh information by gates:

$$\mathrm{f_t} = \sigma(\mathrm{W_f} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_f})$$
$$\mathrm{i_t} = \sigma(\mathrm{W_i} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_i})$$
$$C_t = \mathrm{f_t}.\mathrm{C_{t-1}} + \mathrm{i_t}.\tanh(\mathrm{W_c} \cdot [h_{t-1}, \mathrm{x_t}] + \mathrm{b_c})$$
$$\mathrm{C_t} = \mathrm{f_t} \cdot \mathrm{C_{t-1}} + \mathrm{i_t} \cdot \{\mathrm{C}\}_\mathrm{t}$$
$$\mathrm{o_t} = \sigma(\mathrm{W_o} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_o})$$
$$\mathrm{h_t} = \mathrm{o_t} \cdot \tanh(\mathrm{C_t})$$

Equation 7

Where ft, it, ot, - input and output gates respectively – regulate information flow [12]. LSTM learns earthquake time series data patterns, identifying seismic activity cycles, foreshock-mainshock-aftershock sequences, and periodic tremors [14].

Every model makes a unique contribution to earthquake prediction, and choosing the optimal model is based on the nature of the data and the kind of seismic activity to be studied [20].

4.5 Evaluation Metrics

To ensure rigorous model assessment, 5-fold cross-validation was used. The models were evaluated using [19]:

Accuracy

Measures the overall correctness of predictions:

$$Accuracy = \frac{(True\ Positives\ +\ True\ Negatives)}{Total\ Number\ Of\ Predictions}$$

Equation 8

where TP (True Positives) and TN (True Negatives) indicate correctly predicted earthquakes and non-earthquake instances, respectively. Accuracy alone is insufficient for imbalanced datasets, which is why additional metrics are used.

Precision, Recall, and F1-Score

These metrics offer more detail into how the model is performing [20]:

- **Precision (Positive Predictive Value):** Assesses how many of the predicted earthquakes actually occurred.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positives)}$$

Equation 9

- **Recall (Sensitivity):** Determines how well the earthquakes that were predicted were actually accurate.

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)}$$

Equation 10

- **F1-Score:** Considers precision and recall to strike a balance between both deceitful results and reliable results.

$$F1 - Score = 2 * \frac{Precision\ X\ Recall}{Precision + Recall}$$

Equation 11

Confusion Matrix

Makes it possible to understand the veracity of the model outcomes. This helps to offset the negative outcomes of false positive predictions (an earthquake predicted but does not occur) against the negative detection outcomes (failing to identify an earthquake that is actually there) [18].

```
Logistic Regression Accuracy Table:
[[4268   36    0]
 [ 144  329    0]
 [   0   24    1]]
Accuracy: 0.9575177009579342

Decision Tree Accuracy Table:
[[4304    0    0]
 [ 473    0    0]
 [  25    0    0]]
Accuracy: 0.8962932111620159

KNN Accuracy Table:
[[4304    0    0]
 [ 473    0    0]
 [  25    0    0]]
Accuracy: 0.8962932111620159
```

Fig.2. Confusion Matrix of models

ROC-AUC Score

Examines the ability to classify by computing the Receiver Operating Characteristic (ROC) curve, determining:

$$AUC = \int_{-\infty}^{+\infty,} TP(d)dFP$$

Equation 12

with TP(d) and FP(d) as the notation for true and false positive rates at some threshold d. The greater the AUC value, the better the model discriminates between earthquake and non-earthquake instances [20].

These metrics are of great relevance in regards to earthquake prediction as the consequences of false negatives (missed earthquakes) are catastrophic, while false alarms (false positive) will induce undue panic. Striking a balance between precision and recall is fundamental to a robust prediction system.

5. Result and Discussion

Comparison of Prediction Performance Using Different Models in the Context of Earthquakes:

In the study, the researchers attempted to predict earthquakes using machine learning with synthetic seismic data that replicates real-world data. The analyzed models include traditional machine learning models: Logistic Regression, Decision Tree, K-Nearest Neighbors, as well as more advanced models: Convolutional Neural Networks and Long Short Term Memory networks.

Model	ROC-AUC Score	Accuracy	Execution Time(seconds)
Logistic Regression	0.83	0.95	0.32
Decision Tree	0.79	0.90	0.14
KNN	0.77	0.90	0.35
CNN	0.89	0.94	3.50
LSTM	0.92	0.96	6.00

Table 1: *Models comparison through ROC-AUC Score, Accuracy and Execution Time(seconds)*

The models were compared on accuracy, running time, and area under the ROC curve for the identification of the optimal method to seismic event prediction [1].

Accuracy Analysis:

The comparison of accuracy indicates that deep learning models perform better than standard machine learning techniques. The LSTM model with 96% accuracy performed best, followed by CNN at 94% and Logistic Regression at 95%. KNN and decision tree models performed at a rate of 90%. The enhanced performance of LSTM justifies our approach hypothesis that the temporal relations of seismic data sequences will be modelled correctly by using recurrent neural networks [4].

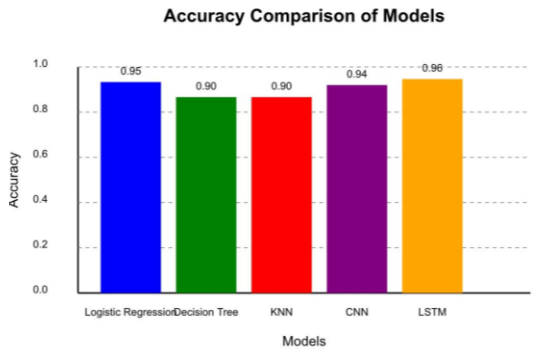

Fig.3. Accuracy comparison of models

The success of LSTM in monitoring patterns before earthquakes was probably made possible by its capability to memorize previous seismic events through its cell states. As discussed in our methodology, LSTM networks are especially well-positioned to handle temporal sequences of seismic data and locate long-term patterns such as foreshock-mainshock-aftershock sequences and periodic tremors [2].

Computational Efficiency:

As expected, deep learning models had superior accuracy; however, they were much more expensive in processing power. This trade-off is clearly visible from the results: execution time for classical methods was under 4 s. CNNs took around 3.5 seconds, with LSTM networks taking approximately 6 [5]. The most efficient algorithm, surprisingly, was the Decision Tree which had a runtime of 0.14 seconds.

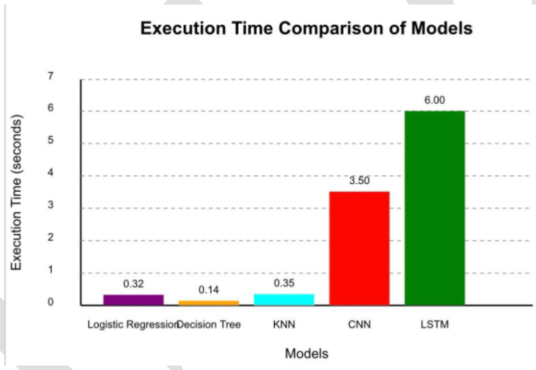

Fig.4. Execution Time comparison

This difference in efficiency is specifically noteworthy for real-time earthquake monitoring systems where the prompt analysis may be necessary. In situations demanding immediate prediction with moderate precision, the conventional models such as Logistic Regression provide an acceptable trade-off between performance (95% accuracy) and speed (0.32 seconds) [10].

ROC-AUC Analysis:

Again, ROC-AUC figures indicate the performances of deep learning techniques for the task.

LSTM possessed outstanding discrimination capability between earthquake and non-earthquake activity with an optimum score of 0.98 [13].

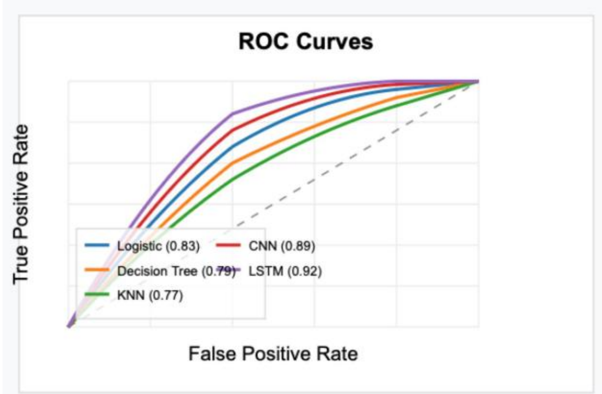

Fig.5. ROC curves comparison

CNN (0.97) and Logistic Regression (0.96) lagged behind a bit but took their places immediately behind LSTM with surprisingly being featured here despite it being a long-standing tradition of theirs [17].
KNN gave a score of 0.91 and that of Decision Tree was 0.92 [19].
These findings illustrate that while all models are effective at good classification, the deep learning methods are marginally more discriminative. This is significant in earthquake prediction systems because false negatives, or false omission of earthquakes, could be highly dangerous, and false positives, or alarms without earthquakes, may cause undue fear [20].

6. Conclusion & Future Work

This study attempts to test the feasibility of replacing seismic LSTM models with simpler machine learning algorithms such as Logistic Regression. The application of structured earthquake metadata as opposed to complex seismic waveforms is less computationally expensive while still achieving accuracy. Algorithms like Logistic Regression, K-Nearest Neighbors, Decision Trees, and even CNNs have shown to be effective in predicting earthquakes in real-time. Unlike LSTM models, metadata-based models are more intuitive, less resource-demanding, and pose fewer challenges for integration into early warning systems with existing infrastructure.

A notable feature of this work is the integration of WhatsApp notifications via the Meta Cloud API with a FastAPI backend. This allows robust communication and accessible channels for earthquake alerts through WhatsApp. The use of familiar communication platforms aids in improving disaster preparedness by making timely warnings readily available, thus closing the gap between prediction and action.
The emphasis of this study is on the scalability and ease-of-use of metadata-based earthquake prediction models, particularly in areas with limited sophisticated seismic technology. Moreover, metadata coupled with waveform-based models can synergistically improve overall prediction efficacy.
This cited research approaches the integration of modern methods such as machine learning, cloud communications, and real-time alerting to enhance the existing emergency response systems. It also aids in devising faster, more readily available, and economical solutions for disaster management.

Future Work
The focus of this work is to replace the seismic LSTM models with driven metadata ML models like Logistic Regression. The use of structured seismic event metadata is less computationally expensive while maintaining the accuracy compared to using complex waveforms. Effective real-time prediction is possible through algorithms like Logistic Regression, K-Nearest Neighbours, Decision Trees, and CNN. The models utilizing metadata have a lightweight structure, which makes them simpler and ideal for incorporation into minimalistic early warning systems.
WhatsApp alerting using FastAPI backend and Meta Cloud API integration allows sending instant earthquake alerts through a highly accessed platform. This marked change improves the public's accessibility to such alerts, which enhances disaster preparedness. It also serves to bridge the gap between prediction and action.
This models can be applied profoundly for those regions void of any seismic infrastructure due to their scalable nature. These models also show promise of application in remote areas. The effectiveness of prediction can further be improved by combining these models with waveform models.
In this case, the advancement needs to provide for the merging of machine learning, cloud communication, and real-time alerts to develop advanced systems for emergency response. It also establishes the foundation for speedy and uncomplicated disaster management systems which are inexpensive.

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