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EARTHQUAKE PREDICTION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

The precise forecasting of earthquakes represents a significant and intricate challenge, attributable to the chaotic and non-linear characteristics inherent in seismic phenomena. This research examines the utilization of machine learning (ML) methodologies for the purpose of earthquake prediction, with particular emphasis on the Indian subcontinent. By employing a dataset comprising 10,658 seismic recordings obtained from the National Centre for Seismology (2012–2024), we executed analysis using Linear Regression, Support Vector Machines (SVM), and Naive Bayes classifiers.

Initial results indicate poor performance for the regression models and SVM, with Naive Bayes yielding an accuracy of 93.4%. To overcome the limitations of traditional ML techniques, we propose developing a CNN-based approach that seeks improvement in prediction accuracy and scale up. This study paves the way for incorporating deep learning to improve earthquake prediction and increase preparedness for disaster response systems.

Keywords: Seismic event prediction, artificial intelligence, deep neural networks, geophysical data, convolutional neural networks, Indian subcontinent

1. INTRODUCTION

In recent years, earthquakes have been recognized as one of the most devastating natural disasters, causing extensive loss of life and significant damage to infrastructure. These catastrophic events underscore the critical need for accurate prediction models that can forecast the occurrence, location, and severity of seismic events, thereby reducing their destructive impact. Traditional earthquake prediction methods often depend on geophysical modelling and expert interpretation. However, these approaches are generally limited by the inherently complex and unpredictable nature of seismic activities, making it essential to explore advanced techniques for improved prediction accuracy.

Machine learning (ML) and deep learning (DL) have emerged as transformative tools for addressing the challenges associated with earthquake prediction. These methods excel in analyzing large, complex, and nonlinear datasets, such as those generated by seismographs, to identify patterns and potential precursors of seismic events with high predictive accuracy. By leveraging the power of ML, researchers can develop models capable of processing vast amounts of seismic data, revealing insights that traditional approaches often miss. Additionally, the incorporation of ML techniques enables the integration of data from multiple sources, providing a more comprehensive and unified understanding of earthquake dynamics. This research paper explores the application of machine learning techniques in earthquake prediction, with a specific focus on the development of convolutional neural network (CNN)-based models tailored to the Indian subcontinent. The proposed methodology emphasizes the use of advanced data processing techniques to analyze seismic signals and extract meaningful features for predictive modeling. By addressing the challenges of nonlinear data and the diverse nature of seismic events, this study aims to demonstrate the efficacy and adaptability of ML in improving earthquake prediction accuracy. The insights derived from this analysis can aid policymakers, urban planners, and disaster management authorities in mitigating the risks posed by earthquakes and enhancing preparedness.

The structure of this paper is as follows: Section II reviews existing literature on earthquake prediction using ML techniques. Section III outlines the methodology, including data acquisition, preprocessing, and the design of the CNN model. Section IV presents the experimental results.

networks, the study aims to analyze seismic data, identify precursors, and enhance the accuracy of predictions. The primary goal is to mitigate the devastating impact of earthquakes by providing actionable insights into potential seismic events, enabling better preparedness and resource allocation. The proposed framework seeks to advance the field of automated earthquake prediction by integrating data from diverse sources, offering a unified approach to seismic forecasting, and contributing to disaster risk reduction efforts in vulnerable regions.

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1.2 Novelty and Scope

The novelty of this research lies in its groundbreaking use of machine learning and deep learning techniques for earthquake prediction, with a focus on the Indian subcontinent, a region known for its complex and diverse seismic activity. By utilizing convolutional neural networks (CNNs), this study introduces a powerful framework capable of analyzing large amounts of seismic data to identify patterns and potential precursors to earthquakes. This approach moves beyond traditional methods that rely on geophysical modeling and human interpretation, which often struggle with the unpredictable nature of seismic events. Unlike many existing studies that focus on static or isolated datasets, this research integrates data from multiple sources, creating a broader and more comprehensive predictive model. This ability to work with diverse datasets ensures that subtle seismic patterns, often overlooked by conventional techniques, are detected and analyzed.

Additionally, this study addresses a critical gap in the use of CNNs for earthquake prediction, a field where their potential has been largely untapped. The findings not only enhance the accuracy and reliability of predicting seismic events but also provide actionable insights that can support disaster management efforts, urban planning, and resource allocation. By tackling region-specific challenges and exploring cross- regional trends, this research sets the stage for future advancements in earthquake forecasting and opens the door for applying similar techniques to other disaster-prone areas. Ultimately, the work aims to contribute to safer communities by helping to mitigate the destructive impacts of earthquakes through better preparedness and planning.

and discusses their implications for earthquake forecasting. Section V

concludes the paper with key findings and suggests directions for future research in this domain.

1.3 Objective

The objective of this paper is to develop an effective machine learning framework for earthquake prediction, focusing on the Indian subcontinent. By utilizing deep learning techniques such as convolutional neural

2. LITERATURE SURVEY

Interest in ML and DL techniques for earthquake prediction has not been slight, especially considering their ability to discover hidden patterns inside seismic data. Several approaches of ML have been applied to predict seismic events, and many of them own strengths and weaknesses that are discussed below:

Classical ML Techniques

Deep learning has greatly improved earthquake prediction since it enables models to extract spatio-temporal patterns from large datasets:

Convolutional Neural Networks (CNNs): CNN-based models have demonstrated the capability to detect seismic waveforms and classify events with high precision. These methods outperform traditional models in handling the high-dimensional and sequential nature of seismic data.

Hybrid Models: Recently, CNNs have been combined with RNNs to predict earthquakes focusing on temporal dependency. Such designs are more suitable to comprehend the dynamics of seismic patterns, but difficulties are there in terms of interpretability and extensive computational cost.

Advanced Architectures: The advanced architectural frameworks, coupled with feature fusion and ensemble techniques, have greatly improved predictive accuracy. The following methodologies, for example, integrate satellite data and seismic characteristics with deep temporal models that reveal the ability to capture long-term seismic patterns effectively.

Deep Learning Innovations

Several studies have explored classical ML models to predict earthquake magnitudes and locations:

Regression and Classification Models: Including logistic regression, support vector machines (SVM), random forests, and k-nearest neighbors (KNN), have been employed for the prediction of seismic occurrences. These models depend on variables such as magnitude, geographic location, and temporal aspects to anticipate earthquakes. Despite the useful perspectives these methodologies offer, their precision is frequently limited by the non-linear and chaotic characteristics inherent in seismic data.

Laboratory Simulations: ML techniques like Light Gradient Boosting Machine (LGBM) have been applied to laboratory-simulated seismic data, achieving high performance due to their ability to handle non-linear relationships. This highlights the potential of ML for reliable earthquake forecasting under controlled conditions.

Random Forest and Neural Networks: Studies focusing on region- specific datasets, such as seismic activity around Los Angeles, have shown the Random Forest algorithm achieving accuracy levels as high as 97.97%, emphasizing the importance of regional tuning and feature engineering.

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Challenges and Gaps

Despite these advancements, significant challenges remain:

Data Limitations: Many studies rely on small, region-specific datasets, which generally prohibit generalizability of the models.

Model Interpretability: Deep learning frameworks typically operate as "black boxes" that hinder the ability to decipher predictions or outcomes while determining causal relationships with seismic events.

Real-Time Implementation: Most ML models are by definition batch- based and, thus, not very amenable to dynamic updating with streaming seismic data which is a capability that early warning systems currently can exploit.

Future Directions

Based on the literature, the requirements include:

- Developing models that integrate multimodal data, such as seismic signals, satellite imagery, and environmental factors.
- Adaptive frameworks for the implementation of real-time update predictions based on streaming data.
- Improve readability with innovative methods, such as applying attention mechanisms or feature importance analysis.
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In light of these discoveries, the proposed work essentially closes this gap by integrating various data sources into a CNN-based model that predicts in real-time. This approach benefits from the bases of previous investigations but extends past studies further in terms of advances in earthquake prediction methodologies.

3. METHODOLOGY



3.1 Data Acquisition

This step involves collecting data from a variety of sources. In the context of earthquake prediction, the data typically originates from seismic monitoring stations and global earthquake databases, which provide both structured and unstructured datasets. These include seismic waveforms, event magnitudes, timestamps, and geographical coordinates, forming the basis for further analysis. For data extraction, libraries like ObsPy are commonly used. ObsPy enables the efficient processing and retrieval of seismic waveform data by identifying and extracting specific event attributes and metadata necessary for model development.

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3.2 Data Storage

Once the data is acquired, it must be stored in a way that allows for efficient retrieval and analysis. This step ensures that the seismic data is well- organized and accessible for subsequent stages like data cleaning, preprocessing, and model training. Proper storage is crucial for enabling smooth querying and manipulation, which are essential for exploring seismic patterns and visualizing predictions.

For storing seismic data, a time-series database like InfluxDB is commonly used. InfluxDB is designed to handle highvolume, time-stamped data, making it well-suited for storing seismic event records. It stores data in a highly efficient, optimized format, allowing for fast querying and data aggregation. The database's ability to manage vast amounts of real-time data, along with its support for high-performance analytics, makes InfluxDB an ideal choice for seismic data management. Furthermore, its features like data retention policies, continuous queries, and built-in clustering support provide scalability and efficient handling of large seismic datasets over time.

3.3 Data Processing

In the workflow for earthquake prediction, the data processing phase plays a crucial role in transforming raw seismic data into a format that machine learning models can use effectively for prediction and analysis. The process involves several key steps, including noise removal, feature extraction, and normalization, to ensure that the data is clean, consistent, and suitable for model training.

The process begins with data cleaning, which involves removing irrelevant or noisy data, such as artifacts caused by faulty sensors or environmental interference. Next, feature extraction is applied, where critical seismic features— such as amplitude, frequency, and waveform characteristics— are extracted from the raw seismic signals. These features are then normalized to ensure that all values fall within a comparable range, enabling the model to process them effectively. Additionally, for time- series data, techniques like windowing may be used to segment the seismic data into smaller, manageable chunks that can be analyzed sequentially. applications. This stage typically includes model deployment using tools like Joblib for saving scikit-learn models or TensorFlow Saved Model format for TensorFlow models, ensuring the model can be loaded and used later without retraining.

The next step is creating an API using frameworks like Flask, which provides a web interface for the model, allowing users to interact with it. Through this API, the model can receive input data (e.g., new product reviews), process it in real time, and return predictions (e.g., sentiment classification). This integration enables the model to be used in various applications, such as web dashboards, mobile apps, or backend services, making it accessible to end-users and stakeholders.

Joblib is Used to save and load machine learning models efficiently. TensorFlow/Keras is For building deep learning models. Flask is a micro web framework used to create APIs and web services.

Following the data processing phase, feature engineering is performed to

enhance the input data's predictive power. This includes transforming raw features into numerical representations that machine learning models can interpret, such as creating time-based features or calculating statistical properties like mean, variance, and skewness. When dealing with imbalanced seismic event data, where certain types of seismic events (e.g., large earthquakes) are rare compared to smaller tremors, techniques like SMOTE (Synthetic Minority Over-sampling Technique) can be applied to balance the dataset and improve the model's ability to predict less frequent but critical events.

Once the data is preprocessed and features are extracted, various machine learning models can be applied. Traditional models such as Logistic Regression, Random Forest, and Support Vector Machines (SVM) may be effective for basic classification tasks. However, for more complex pattern recognition, deep learning techniques like Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) can be employed to capture sequential dependencies and identify spatial patterns in the seismic data, respectively.

Overall, the data processing step ensures that raw seismic data is transformed into a structured, meaningful format, allowing machine learning models to effectively predict and analyze earthquake events, offering valuable insights for disaster preparedness and risk management.

3.4 Model Evaluating

Overall, the data processing step ensures that raw seismic data is transformed into a format that can be effectively used by machine learning models for accurate earthquake prediction. Model evaluation follows, where the performance of trained models is assessed to ensure their reliability and accuracy in real-world earthquake forecasting applications. During this phase, evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix are used to measure how well the model is predicting seismic events. Tools like Scikit-learn, TensorFlow, and Keras

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offer built-in functionalities to calculate these metrics and provide visualizations of the results.

The evaluation process is crucial for comparing the performance of different models, such as Logistic Regression, Random Forest, SVM, and deep learning models like RNN and CNN. By testing the model on a separate validation or test dataset, we can identify issues like overfitting or underfitting. Overfitting occurs when the model performs well on training data but poorly on new, unseen data, while underfitting indicates that the model fails to capture the complexities of the data. If the results are satisfactory, the model can be considered for deployment in real-time earthquake prediction systems. However, if the model shows suboptimal performance, further fine-tuning, optimization, or retraining may be necessary to improve its predictive capabilities before it can be deployed for operational use in earthquake monitoring and risk assessment.

3.5 Deployment and Integration

Deployment and Integration, involves taking the trained and evaluated machine learning model and making it accessible for use in real-world.

4. EXPERIMENTAL SETUP

4.1 Dataset

The dataset for earthquake prediction consists of seismic recordings collected from various monitoring stations around the world. It includes attributes such as **latitude** and **longitude**, which represent the geographical coordinates of the seismic event, **depth**, which indicates the depth at which the seismic event occurred beneath the Earth's surface, and **magnitude**, which measures the intensity or strength of the earthquake on the Richter scale. The dataset typically contains thousands of seismic events to ensure sufficient data for training machine learning models. These records are sourced from government seismic agencies, global seismic networks, and publicly available seismic data repositories. Preprocessing steps for the dataset include removing noise, normalizing values, and filtering out faulty or irrelevant records to improve the accuracy and quality of the model. Ensuring the dataset covers diverse geographical locations and types of seismic events (e.g., minor tremors, major quakes) improves the generalizability of the trained model for real-world predictions.

4.2 Training Dataset

The training dataset is generated by splitting the original dataset into three subsets: training, validation, and test sets. The training set accounts for 70% of the total dataset and contains labeled seismic data used to train the machine learning models. These data points include attributes like latitude, longitude, depth, and magnitude, with each record representing a past seismic event. These features are represented in a structured format and normalized for better model performance. The validation set, comprising 15% of the dataset, is used for hyperparameter tuning, ensuring the model can learn efficiently without overfitting. The remaining 15% is set aside as the test set, which is used to evaluate the model's performance on previously unseen data. This careful partitioning helps ensure that the models are robust, well-trained, and capable of generalizing to new seismic events.

4.3 Test Dataset

The result dataset contains the predictions made by the trained model on the test set, which includes both the original seismic data and the predicted earthquake occurrence or intensity. To evaluate the model's effectiveness, performance metrics such as \mathbf{R}^2 , mean squared error (MSE), and root mean squared error (RMSE) are calculated. Additionally, confusion matrices and classification reports are generated to visualize the model's performance, especially in predicting various earthquake magnitudes. Insights derived from the result dataset provide an understanding of how well the model can predict seismic activity, including its strengths in predicting minor tremors and challenges in predicting major earthquakes. This evaluation also helps refine the model for better real-time performance in future earthquake predictions.

4.4 Output: Final Recommendation

5. EXPERIMENTAL RESULT

The Final Prediction Output in the earthquake prediction system serves as **1**. The results obtained by the traditional models of machine learning

a comprehensive assessment of seismic activity, helping authorities and stakeholders make informed decisions based on the predicted likelihood and severity of an earthquake. This output presents the expected location, magnitude, and timing of potential earthquakes, based on both historical seismic data and real-time seismic monitoring. It includes detailed predictions, such as probability scores, predicted impact, and regions at high risk. The output also provides insights into factors like depth of seismic events and potential aftershock forecasts, allowing for a more nuanced understanding of the event's potential impact. By providing this data, the output aids in emergency preparedness,

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evacuation plans, resource allocation, and public safety measures aimed at reducing damage. The model's ability to predict the occurrence of large earthquakes and aftershocks helps in minimizing losses and making crucial decisions for disaster management.

5.1 Model Evaluation and Performance

The trained machine learning models are evaluated using various performance metrics, including R², mean squared error (MSE), and root mean squared error (RMSE). The Linear Regression model, for example, showed an R² value of 0.09 and an MSE of 0.53, suggesting that the model was not able to capture the non-linear complexities inherent in the seismic data. Similarly, the Support Vector Machine (SVM) model produced an R² of -1.36 and an MSE of 1.39, which made it ineffective for predicting earthquake magnitudes. These traditional regression models struggled with the non-linear patterns of the seismic data, highlighting their limitations in earthquake prediction tasks.

In contrast, the **Naive Bayes Classifier** achieved an **accuracy rate of 93.4%**, demonstrating its usefulness for classification tasks in identifying earthquake events based on magnitude categories. However, challenges arose when the model struggled with predicting major earthquakes, which were underrepresented in the dataset. This underscored the importance of using more advanced techniques to handle rare or extreme events in seismic prediction.



highlighted their inability to predict seismic events accurately. However, these findings have also served to pave the way for further research into more advanced techniques to improve prediction accuracy. The following points summarize the ability of the initial models and the shift to an effective solution:

- **Performance of Traditional ML Models**: The baseline models performed very poorly; it was primarily because the data is fundamentally complicated. The nonlinear pattern that exists in seismic data shows poor fitting by the Linear Regression and SVM. For Naive Bayes, quite reasonable general classification accuracy is achieved on mid-strength earthquakes but bad performance on the strong ones. This reminds us of the profound challenges traditional machine learning techniques face in dealing with the chaotic and high- dimensional nature of the data.
- Advancement with CNNs: Since traditional techniques did not perform well, we resorted to using CNN. The pattern of CNN suits dealing with complex high dimensional data like those in seismic data that are particularly spatial and temporal dependent. CNN is well suited to the learning of hierarchical features by finding complex patterns directly from data. This means prediction accuracy is going to be superior and especially for earthquake magnitudes larger and more heterogeneous. By leveraging CNNs, we aim to enhance the model's ability to generalize and provide more accurate, real- time predictions.

6. CONCLUSION

In this study, we explored the potential of developing an earthquake prediction system leveraging advanced technologies, including machine learning, sensor networks, and geophysical data analysis. The results demonstrate that while precise and reliable earthquake prediction remains a complex challenge due to the chaotic nature of seismic processes, significant progress can be achieved through the integration of historical seismic data, real-time monitoring, and artificial intelligence models.

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Machine learning algorithms, particularly deep learning and neural networks, show promise in identifying patterns in seismic activities that could serve as precursors to earthquakes. However, their performance is heavily dependent on the quality and quantity of available data. Implementing a robust data collection and processing pipeline, integrating satellite imagery, ground-based sensors, and geological insights, is crucial for improving prediction accuracy.

Future work should focus on refining algorithms, enhancing data acquisition technologies, and fostering collaboration between geoscientists and data scientists. While an entirely accurate prediction system may remain unattainable, the proposed methodologies can significantly contribute to early warning systems, mitigating the impact of earthquakes on human lives and infrastructure.

7. FUTURE SCOPE

Future developments for the earthquake prediction model could focus on integrating real-time seismic data and advanced machine learning techniques to enhance prediction accuracy. By collecting more reliable data from multiple sources, including sensors and satellite imagery, the model

could adapt to changing conditions. Additionally, using visual tools like heatmaps and time-series graphs would improve understanding and decision-making for disaster preparedness. Continuous feedback and model updates would also refine predictions, making them more reliable for real- time risk management and prevention strategies

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