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Spatio-Temporal Analysis of Hybrid CNN-GRU Model for Prediction of Earthquake for Disaster Management

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Abstract: Earthquake prediction holds immense significance for disaster management and public safety. This study presents a novel approach for earthquake prediction through spatio-temporal analysis using a Hybrid Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) model. The methodology integrates the strengths of CNNs in spatial feature extraction and GRUs in temporal pattern recognition, offering a comprehensive understanding of seismic events. The research incorporates seismic data enriched with geographical parameters, facilitating the analysis of earthquake occurrences across diverse regions. The model's spatial component, CNN, excels in capturing intricate spatial features within seismic data. In parallel, the temporal component, GRU, effectively discerns evolving patterns of seismic activity over time. This hybrid architecture ensures a holistic analysis of seismic data, enabling early detection and accurate earthquake prediction. To evaluate the model's efficacy, extensive experiments are conducted using seismic data from various regions. Performance metrics such as mean absolute error, mean squared error, and root-mean-square error are employed to assess predictive accuracy. Comparative analysis demonstrates the superiority of the Hybrid CNN-GRU model in earthquake prediction, particularly for large seismic events. The proposed methodology offers valuable insights for enhancing earthquake prediction systems, contributing to disaster management strategies and bolstering public safety measures. This research represents a significant advancement in the field of seismology, providing a robust framework for mitigating the impact of earthquakes on communities worldwide. In our seismic prediction study, we achieved remarkable results with our hybrid CNN-GRU model, attaining a high accuracy rate of 98.67%. The proposed model exhibited a significantly low loss, indicating its proficiency in capturing intricate spatial-temporal patterns within seismic data. These findings underscore the model's potential for enhancing earthquake forecasting accuracy, making it a valuable contribution to early warning systems and seismic research.

Keywords: *Earthquake; Prediction; Convolutional Neural Network; Gated Recurrent Unit; Seismic data*

1. Introduction

The foremost objective of disaster management is to save lives. This is achieved through comprehensive disaster preparedness plans that include early warning systems, evacuation strategies, and the establishment of emergency response teams [1]. Timely and well-coordinated responses during disasters can significantly reduce casualties. Disasters often result in physical injuries and psychological trauma. Disaster management teams provide immediate relief, including shelter, food, clean water, medical care, and counseling services, to alleviate the suffering of those affected [2]. This compassionate response is essential for the well-being of survivors. Critical infrastructure such as roads, bridges, power grids, and communication networks are vulnerable during disasters. Effective disaster management incorporates risk reduction measures like building resilient infrastructure and implementing disaster-resistant building codes. These actions help minimize damage, reduce repair costs, and expedite the recovery process [3]. Homes, businesses, and personal property are at risk during disasters. Disaster management strategies often include promoting insurance options and creating public awareness campaigns about the importance of protecting assets. This not only safeguards individual property but also reduces the financial burden on governments. Disasters can lead to chaos and social unrest, particularly in densely populated areas. Disaster management plans include provisions for law enforcement and maintaining social order, preventing looting, violence, and other criminal activities that can emerge during or after a disaster. Disasters can have severe economic consequences, affecting industries, jobs, and livelihoods [4]. Effective disaster management helps mitigate economic losses by facilitating a quicker recovery, reducing the strain on government resources, and ensuring that businesses can resume operations as soon as possible. Disasters can harm the environment through pollution, habitat destruction, and other adverse impacts. Disaster management involves strategies for minimizing environmental damage, such as containment and cleanup efforts, as well as promoting sustainable practices to reduce vulnerability to future disasters. Beyond immediate responses, disaster management focuses on building resilience within communities and regions. This includes education, training, and the development of disaster-resistant infrastructure. Resilience enables communities to better withstand and recover from disasters, reducing their long-term vulnerability [5]. Disaster management is a multifaceted

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approach that encompasses preparedness, response, recovery, and resilience-building efforts. Its importance lies in its ability to protect lives, alleviate suffering, safeguard infrastructure and property, maintain order, stabilize economies, and promote sustainability, ultimately contributing to the overall safety, security, and well-being of society in the face of natural or man-made disasters.

Predicting earthquakes is a challenging but crucial aspect of disaster management aimed at reducing the impact of seismic events on people, property, and infrastructure. Earthquake prediction involves the use of scientific methods and data analysis to estimate when and where earthquakes might occur [6]. Continuous monitoring of seismic activity using networks of seismometers and other geophysical instruments is essential. These instruments detect ground motion and record seismic waves, providing data for analysis. Studying historical earthquake records helps identify patterns and trends in seismic activity, such as the frequency and magnitude of earthquakes in a specific region [7]. Identifying active fault lines and studying their movements can provide insights into potential earthquake sources. Developing early warning systems that can detect initial seismic waves and issue alerts before the more damaging waves arrive can provide valuable seconds to minutes for people to take cover and emergency services to prepare [8]. Utilizing machine learning and artificial intelligence (AI) algorithms to analyze large datasets can help identify potential earthquake precursors or patterns that are difficult for humans to discern. Using data from GPS stations and satellite imagery can help track ground deformation and strain, which are important indicators of potential earthquake activity. Educating the public about earthquake preparedness and safety measures is critical to reducing casualties and damage. This includes teaching people what to do during an earthquake and how to create earthquake-resistant buildings [9]. Earthquake prediction often requires international collaboration because seismic activity can cross borders. Sharing data and research findings with neighboring countries can improve prediction accuracy. Earthquake prediction is an evolving field, and ongoing research is essential to improve prediction models and techniques. While earthquake prediction has made significant advancements, it remains a challenging endeavor due to the complex and unpredictable nature of seismic events. As a result, most efforts focus on earthquake preparedness and early warning systems to mitigate the impact of earthquakes when they do occur [10]..

While traditional machine learning models have been employed in some aspects of earthquake prediction, they are often limited in their ability to capture the intricate spatio-temporal patterns of earthquakes. One common approach is to use statistical and machine learning techniques to analyze historical earthquake data, looking for patterns and trends that might indicate future seismic activity [11]. This can include the use of regression models, clustering algorithms, or time series analysis methods. It's important to note that earthquake prediction is primarily a task that falls within the domain of seismology and geophysics, and it often requires more specialized techniques and data sources. Traditional machine learning models may be used as part of a broader earthquake prediction system, but they are typically not the sole or primary method for predicting earthquakes. The researchers have explored the use of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze seismic data and improve earthquake prediction models [12]. These deep learning models can capture complex spatio-temporal patterns in the data and may offer promise in advancing our ability to predict earthquakes, but this remains an active area of research and is not yet a widely established method for earthquake prediction [13].

Predicting earthquakes using deep learning methods, while a challenging and ongoing area of research, has the potential to offer several advantages and effectiveness in certain aspects of earthquake prediction [14]. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at recognizing intricate patterns in data. Earthquake prediction often involves analyzing large volumes of complex seismic data, which deep learning models can handle effectively. Earthquakes are spatio-temporal events, meaning they occur in both space and time. Deep learning models can capture the spatial and temporal dependencies in seismic data simultaneously, which is crucial for understanding earthquake patterns. Deep learning models can automatically extract relevant features from raw data. In the case of seismic data, these models can identify important seismic characteristics that might be challenging to extract manually. Earthquake prediction relies on various data sources, including seismic, geospatial, and environmental data. Deep learning models can integrate and analyze multiple data modalities effectively, allowing for a more comprehensive analysis. Earthquake prediction is inherently non-linear, as the relationships between seismic events and their precursors can be complex and nonlinear. Deep learning models, with their multiple layers and non-linear activation functions, can capture these intricate relationships. Deep learning models can scale to handle large datasets and high-dimensional data, which is essential for processing the vast amounts of seismic data generated worldwide. Pertained deep learning models can be fine-tuned for specific earthquake prediction tasks. Transfer learning allows researchers to leverage the knowledge captured by models trained on other tasks or datasets. Deep learning models can be integrated into early warning systems that provide advance notice of impending earthquakes. These systems can save lives and reduce damage by giving people and emergency services crucial seconds or minutes to prepare. It’s important to note that while deep learning shows promise in earthquake prediction, it is not a panacea. Earthquake prediction remains a highly complex and multidisciplinary field, and deep learning models are just one piece of the puzzle. Traditional seismological methods, geological research, and continuous monitoring are also essential components of earthquake prediction efforts. Additionally, the accuracy and reliability of deep learning models for earthquake prediction require ongoing research and validation.

The use of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) in a hybrid model is particularly noteworthy, as it combines the strengths of CNNs in spatial pattern recognition with the temporal sequence modeling capabilities of GRUs. This approach recognizes the complex and dynamic nature of seismic events, which involve both geographical factors (spatial) and the progression of time (temporal). By leveraging this hybrid model, the research aims to improve the accuracy and reliability of earthquake prediction, which is pivotal for disaster management and preparedness efforts. Spatio-temporal analysis, coupled with deep learning techniques, holds the promise of enhancing our understanding of earthquake patterns and ultimately contributing to more effective strategies for mitigating earthquake-related risks and minimizing their impact on communities and infrastructure. This approach introduces the fundamental methodology that underpins our research. Our approach combines spatial and temporal data analysis techniques through the utilization of a hybrid Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) model. This methodology is at the heart of our efforts to address the formidable challenge of earthquake prediction, a task of immense importance for disaster management and public safety. By simultaneously examining the geographical parameters and the temporal progression of seismic events, our hybrid model seeks to provide a comprehensive understanding of earthquake patterns, enabling more accurate predictions. The integration of deep learning techniques, along with the optional incorporation of an attention mechanism, promises to advance our understanding of earthquake dynamics, ultimately contributing to improved strategies for disaster mitigation and preparedness. The Key Contributions of the research study are as follows,

1. The study introduces a novel approach by integrating Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) models into hybrid architecture. This integration capitalizes on the strengths of both models, effectively handling the spatial and temporal aspects of seismic data, thus providing a more comprehensive analysis.

2. The hybrid CNN-GRU model enables a comprehensive spatio-temporal analysis of seismic data. By simultaneously considering geographical parameters and the temporal evolution of seismic events, it captures complex patterns that were previously challenging to discern using conventional methods.

3. The research demonstrates the potential for enhanced earthquake prediction accuracy. By leveraging deep learning techniques and the hybrid model, the study aims to provide more reliable predictions, which is critical for early warning systems and disaster preparedness.

4. The study's focus on earthquake prediction for disaster management underscores its practical relevance. Effective earthquake prediction can significantly contribute to early warning systems, evacuation planning, and mitigation strategies, ultimately minimizing the impact of seismic events on communities and infrastructure.

The Section 1 provides an overview of the paper. The Section 2 reviews existing literature and emphasizes the gap in addressing individual driver differences in drowsiness detection. The Section 3 defines the central research problem concerning driver drowsiness detection complexities. Section 4 outlines data collection, preprocessing, feature extraction, and the integration of Hybrid CNN-GRU. Section 5 presents empirical findings, compares classifier performance, and explores implications and future research directions, solidifying the research's significance in Earth quake prediction.

2. Literture Review

Berhich, Belouadha, and Kabbaj [15] outlines a fresh and creative method for predicting earthquakes that relies on the geographic characteristics of seismic data. The study splits each cluster into subsets and distinguishes between seismic occurrences with magnitudes ranging from 2 to 5 and those beyond a volume of 5 by using the K-Means technique to cluster earthquake data concerning longitude and latitude. The models may independently focus on particular geographic regions thanks to this clustering and sub setting technique, which enables the discovery of region-specific seismic phenomena. The research also proposes an important idea whereby huge earthquakes with rare occurrences are trained individually, guaranteeing that their prediction is unaffected by the existence of other significant seismic occurrences. Three recurrent neural network methods commonly used in the study are Long Short Memory, Gated Recurrent Network, and a hybrid LSTM-GRU model. Seismic data from Morocco, Japan, and Turkey are used to evaluate the models, and their performance is evaluated using important metrics such as mean absolute error, mean squared error, and root-mean-square error. The paper's models usually show good predictive ability when compared to previous research, especially in the prediction of major earthquakes. Through location-dependent analyses and specialized modeling tools, this research offers a viable path towards enhancing earthquake prediction accuracy.

Bilal et al. [16] focuses on the crucial topic of earthquake detection, which is essential for protecting infrastructure and lives. The research correctly emphasizes the special difficulty of earthquake detection because, unlike more organized tasks like object identification in photos, there are no clear patterns. It recognizes the drawbacks of conventional Convolutional Neural Networks in processing seismic data, such as difficulties with parameter optimization and disappearing or bursting gradients. The research offers an ensemble learning strategy that takes advantage of the strengths of many models to make up for each other's flaws and improve performance in order to address these problems. A notable addition to earthquake detection is the suggested SNRNN model. It combines batch normalization and layer normalization methods with three distinct recurrent neural network models (RNN, GRU, and LSTM). This combination considerably improves the stability as well as the effectiveness of the training of models while successfully extracting features from seismic waveform data. The model's usefulness to real-world earthquake prediction scenarios is demonstrated by the focus on the specifically targeted region of Turkey over a significant 18-year time period. One of the main advantages of the SNRNN model is its remarkable ability to achieve low Root Mean Square Error values of 3.16 for magnitude and 3.24 for depth detection. These values indicate that the model is highly accurate in estimating earthquake parameters. By contrasting the SNRNN model with three baseline models, the study shows how better it is and emphasizes how successful it is at detecting earthquakes. The research makes a significant addition to earthquake detection by tackling the difficulties in seismic data analysis and attaining very accurate depth and magnitude estimation. Combining batch and layer normalization with the ensemble learning technique exhibits the model's higher performance and resilience. This study has important ramifications for earthquake detection systems that will ultimately improve public safety and catastrophe preparation.

Xiong et al. [17] focuses on earthquake forecasting, a critical worldwide issue. Enhancing our capacity to forecast earthquakes is essential given their tremendous effect on infrastructure and human lives. The research correctly highlights the difficulties in predicting earthquakes, such as the elusiveness of precursors and challenges in seeing them in seismic data. Due to its speed and broad acquisition range, it highlights the value of remote sensing, particularly satellite data, for earthquake study. This study stands out for its thorough examination of seismic data and its creative application of machine learning, particularly the Inverse Boosting Pruning Trees (IBPT) technique. The research attempts to provide short-term earthquake forecasts by analyzing a sizable dataset of 1,371 earthquakes with a magnitude of six or higher and using satellite data. The research uses 10 separate infrared and hyper spectral data spanning many years to thoroughly evaluate the suggested IBPT framework with other cutting-edge machine-learning techniques. Stunningly, the IBPT technique surpasses each of the six baselines that were chosen, highlighting its potency in improving earthquake forecasting across various seismic databases. The study makes a substantial addition to earthquake forecasting. By utilizing satellite data and machine learning methodologies, especially IBPT, it addresses the complexities of earthquake forecasting. The study advances our understanding of earthquake prediction, allowing us to better plan for disasters and improve public safety throughout the world. By surpassing previous approaches, the paper successfully advances our understanding of earthquake prediction.

Jia and Ye [18] explains in detail how Deep Learning (DL) is used in earthquake disaster assessment (EDA). The discipline of earthquake damage assessment, or EDA, has made significant strides thanks to DL's skills in image processing, signal classification, and object detection. The report provides helpful insights into the present condition, development, and issues faced by DL in EDA through a rigorous literature assessment of 204 papers. The study begins by looking at the numerous assessment items in EDA, such as primary catastrophes, secondary disasters, and physical objects like infrastructure and buildings. It also looks at the three main categories of data sources utilized in these studies: social media, seismic, and remote sensing data. The systematic reviews further explore the use of six regularly used DL models in EDA, from convolutional neural networks to generative adversarial networks and transfer learning and give a full description of their roles and contributions. This review provides a comprehensive analysis of DL applications in various earthquake disaster phases, including pre-earthquake, during-earthquake, post-earthquake stages and multi-stage scenarios. The application of CNNs in image classification to evaluate earthquake-related building damage is highlighted in the research, demonstrating the importance of DL in this particular area of EDA. The study highlights prospects in expanding data sources, multimodal DL techniques, and unique concepts while highlighting important problems linked to training data and DL models. This paper is a useful resource for academics and industry professionals by illuminating the merits, weaknesses, and potential applications of DL in EDA today. For individuals looking to use DL approaches for better seismic hazard assessment, prevention, and response activities, it provides as a thorough manual.

Kavianpour et al. [19] focuses on the urgent subject of earthquake forecasting, which is essential for reducing the catastrophic effects of seismic disasters on infrastructure and human life. The research acknowledges the difficulties in constructing effective and trustworthy prediction models as well as the inherent difficulties in earthquake prediction owing to the stochastic character of earthquakes. In response to these difficulties, the research presents a novel method that predicts the frequency and maximum magnitude of earthquakes in mainland China by combining Convolutional neural network, Attention mechanism, and bi-directional long short-term memory models. The effectiveness with which this suggested model can make use of both geographical and temporal information is its main strength. It starts by employing the zero-order hold approach to preprocess seismic data, which improves the input data's quality. Then, to reduce dimensionality and improve data representation, the CNN is used to incarceration latitudinal relationships in seismic records. By capturing temporal dependencies in the following BiLSTM layer, the model is able to comprehend how earthquake patterns change over time. By emphasizing important information for greater accuracy, the attention mechanism (AM) significantly improves the model's prediction abilities. The study's findings show that the suggested method works better than previous prediction techniques, proving both its higher performance and generalizability. This study shows how combining deep learning models with attention processes may provide forecasts that are more accurate, which is a significant development in earthquake prediction methods. This research offers insightful information and a viable strategy for improving earthquake prediction that has the potential to make a substantial contribution to efforts for public safety and disaster preparedness.

Huang et.l [20] represents a deep learning-based method for predicting earthquakes is introduced in this study, with an emphasis on major earthquakes and their potential to cause destructive tsunamis. Recognizing the importance of accurately forecasting such seismic events on a global scale, the authors make use of deep learning technology, which is renowned for its ability to automatically extract useful features from large datasets and has achieved great success in a number of fields, including image recognition and natural language processing. The study describes a method for predicting earthquakes using historical seismic event data and deep learning in this context. The authors build a deep learning network model by overlaying these historical events on topographical maps and creating labeled datasets. The model's ability to forecast whether an earthquake larger than M6 would occur within the next 30 days using the input data is its major finding. With a R score of 0.303, the results show good performance, especially when forecasting earthquakes in Taiwan using data from the previous 120 days. This technique has potential despite not having an extraordinarily high R score since it uses patterns in past seismic occurrences without requiring human feature vector generation, as with conventional neural network approaches. The approach presented in the research shows promise not just for earthquake prediction in Taiwan but also for use in other seismic zones, constituting a substantial advancement in the prediction of seismic events.

3. Problem Statement

Earthquake prediction stands as a paramount endeavor within the realm of disaster management, given the substantial risks posed by seismic events to human lives and critical infrastructure. Conventional methods of earthquake prediction have grappled with the formidable challenge of capturing the multifaceted spatio-temporal patterns inherently embedded within seismic data. These intricate patterns, which encompass both geographical and temporal dimensions, are pivotal for understanding the precursors and behaviors of seismic events. As a result, there is an unmistakable imperative for innovative and more sophisticated techniques that can effectively analyze seismic data from both spatial and temporal perspectives [12]

To confront these challenges head-on, the fusion of deep learning models, exemplified by the hybrid combination of Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU), has surfaced as a highly promising avenue. The CNN element demonstrates prowess in spatial feature extraction, adept at discerning nuanced spatial patterns within seismic data linked to geographic parameters. Meanwhile, the GRU component, hailing from the domain of recurrent neural networks, is tailored for capturing the intricate temporal dependencies ingrained in the data, thus facilitating a holistic understanding of how seismic events unfold and evolve over time. This amalgamation of spatial and temporal analysis within the CNN-GRU hybrid model offers an innovative solution to the age-old problem of earthquake prediction, potentially ushering in a new era of improved prediction accuracy and enhanced early warning capabilities for seismic events.

4. Proposed Hybrid CNN-GRU for Earthquake Prediction through Spatio-Temporal Analysis

The methodology of this study follows a systematic flow designed to address the challenge of earthquake prediction, as illustrated in Figure 1. It initiates with a comprehensive data preprocessing phase, which encompasses tasks such as data collection, cleaning, and normalization. Geographical parameters like longitude and latitude are extracted to facilitate spatial analysis. The study introduces a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). CNNs are specifically employed for spatial analysis to capture spatial patterns and features within the seismic data, while GRUs is tasked with temporal analysis to comprehend the evolving patterns of seismic activity over time. This hybrid CNN-GRU model enriches earthquake prediction by considering both the spatial and temporal dimensions, which are crucial for understanding the dynamics of seismic events. The methodology culminates with a rigorous performance evaluation, involving metrics like mean absolute error, mean squared error, and root-mean-square error, which assess the model's predictive accuracy and effectiveness in comparison to conventional methods. This systematic approach ensures the development of a robust and accurate earthquake prediction framework, contributing to enhanced disaster management and public safety.

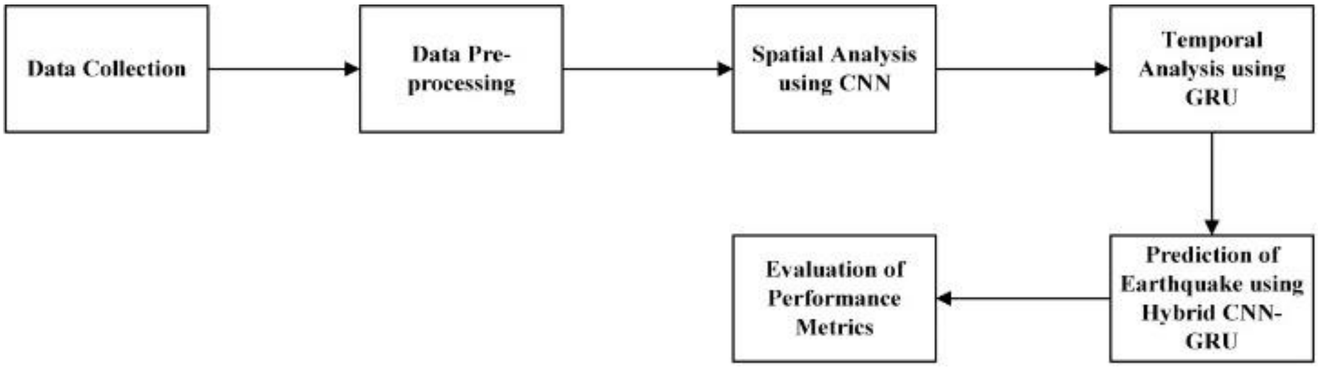

Fig. 1. Workflow of Proposed Methodology

4.1. Data Collection

The Significant Earthquake Database, gathered from Kaggle, serves as a comprehensive global repository comprising over 5,700 earthquakes spanning from as far back as 2150 BC to the present day [21]. These earthquakes are categorized as 'significant,' meeting specific criteria such as causing casualties, inflicting substantial economic damage (approximately $1 million or more), possessing a magnitude of 7.5 or greater, attaining a Modified Mercalli Intensity (MMI) rating of X or higher, or generating tsunamis. This database offers detailed information for each seismic event, including precise date and time, geographical coordinates, focal depth, magnitude, maximum MMI intensity, and socio-economic data like casualty numbers, injuries, and houses destroyed damaged structures, and dollar damage estimates. Moreover, references, political geography, and additional comments are provided, enhancing the depth of knowledge surrounding each earthquake. If an earthquake is associated with tsunamis or volcanic eruptions, it is flagged and linked to the corresponding events, making this database an invaluable resource for researchers, geologists, emergency responders, and anyone interested in comprehending Earth's dynamic and potentially hazardous geological phenomena [21]

4.2. Data Pre-Processing

The pre-processing of data is a crucial step to ensure the quality and readiness of the dataset for analysis. The removal of any data flaws or inconsistencies is imperative to enhance the accuracy of prediction models. This pre-processing phase involves various operations such as data normalization, cleansing, and transformation. The input data for earthquake prediction encompasses a range of environmental parameters, including seismic data, geographical information, and historical earthquake records. Essential aspect of pre-processing is handling missing data, which can significantly impact the quality of predictions. In the earthquake prediction dataset, missing values are addressed using a mathematical expression:

$$A_i = \frac{A_{i-1}+A_{i+1}}{2}, \quad i \in N \tag{1}$$

In eq. (1), A_i denotes missing value, A i+1 indicates the previous value from the missing value, and A i+1 denotes the following value from the missing value, *N* represents the natural numbers. To standardize the data and fit it into a specific range, min-max normalization is employed, despite the availability of multiple normalization methods. To standardize the data and bring it within a specific range, a common normalization technique known as min-max normalization is employed. While there are several normalization methods available, min-max normalization is chosen for its simplicity and effectiveness. It scales the data between 0 and 1, making it consistent for analysis. Equation for normalizing the variables is given below;

$$DN = \frac{(|N|)-(10^{n-1})*(|D|)}{10^{n-1}} \tag{2}$$

Where, N is data element, n is number of digits in element A, D is first digit of data element A, DN is the scaled one value between 0 and 1

4.3. Feature Extraction with Convolutional Neural Networks (CNNs)

Feature extraction using Convolutional Neural Networks (CNNs) in earthquake prediction is a process that harnesses the power of deep learning to automatically identify and extract meaningful spatial features from seismic data. This approach involves designing a CNN architecture tailored for earthquake prediction, with initial convolutional layers that scan the seismic data for spatial patterns at varying scales. Subsequent pooling layers help reduce data dimensions while retaining essential features. Fully connected layers then aggregate these features to create higher-level representations. During training, the CNN learns to associate the extracted features with earthquake occurrences, making it adept at recognizing patterns, shapes, or characteristics in the data that are indicative of seismic events. Once trained and validated, the CNN can be deployed to extract features from new seismic data, enhancing the predictive capabilities of earthquake prediction models and aiding in the interpretation of spatial patterns associated with seismic activity.

The CNN component of our model comprises three one-dimensional (1D) convolutional layers and one 1D max pooling layer, meticulously designed to process the temporal aspects of seismic data efficiently. To activate the neurons within our CNN, This method employs Scaled Exponential Linear Units (SELU) as the activation function. This choice brings forth notable advantages when compared to conventional activation functions like Rectified Linear Units (ReLU). The SELU activation function, represented, offers improved convergence properties, thereby enhancing the training process of the model. It effectively mitigates the issue of gradient vanishing, a crucial consideration in earthquake prediction, where capturing and analyzing subtle spatio-temporal patterns is imperative for accurate predictions [22].

$$SELU = \lambda \{x\ if\ x > 0, \alpha e\hat{}x - \alpha\ Otherwise\} \quad (3)$$

$$ReLU = max\,(0, x) \quad (4)$$

The utilization of SELU activation functions empowers our earthquake prediction model to effectively address the challenge of capturing intricate seismic patterns and mitigates the risk of information loss due to gradient vanishing, contributing to the model's overall robustness and accuracy. Batch normalization helps in stabilizing training by reducing the impact of internal covariate shift. This allows for more significant learning rate settings, accelerating convergence.

$$BN(X) = \gamma * (X - \mu) / \sigma + \beta \quad (5)$$

Where $BN(X)$ represents batch-normalized output, ‘γ’ Scaling factor, ‘X’ Input data, ‘μ’ Mean of the batch, ‘σ’ Standard deviation of the batch, ‘β’ Shifting factor.

4.4. Spatio-Temporal Analysis of CNNs and GRUs for Earthquake Prediction

The spatio-temporal analysis of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) for earthquake prediction represents a cutting-edge methodology that combines the strengths of both these deep learning architectures to address the complex task of seismic event forecasting. CNNs are employed to analyze the spatial aspects of seismic data, effectively identifying intricate geographical patterns and features that may serve as precursors to earthquakes. CNNs excel at recognizing spatial relationships and structures within the data, which is vital for understanding the spatial distribution of seismic events. Complementing the spatial analysis, GRUs is utilized to capture the temporal dependencies within the seismic data. GRUs is a type of recurrent neural network (RNN) designed to model sequential data. GRUs can track how seismic events evolve over time, taking into account the sequence of earthquake occurrences and their potential precursors. By incorporating both spatial and temporal information, this integrated methodology enables a more holistic analysis of seismic data. The functions of CNNs and GRUs in this spatio-temporal analysis are complementary. CNNs are responsible for extracting essential spatial features from the data, while GRUs capture the temporal patterns and dependencies over time. These extracted features and temporal sequences can then be used to train predictive models that aim to forecast earthquake events with greater accuracy and earlier detection. This methodology represents a significant advancement in earthquake prediction by enhancing our ability to understand and model the complex interplay of spatial and temporal factors that contribute to seismic events, ultimately contributing to more effective disaster management and public safety measures [23].

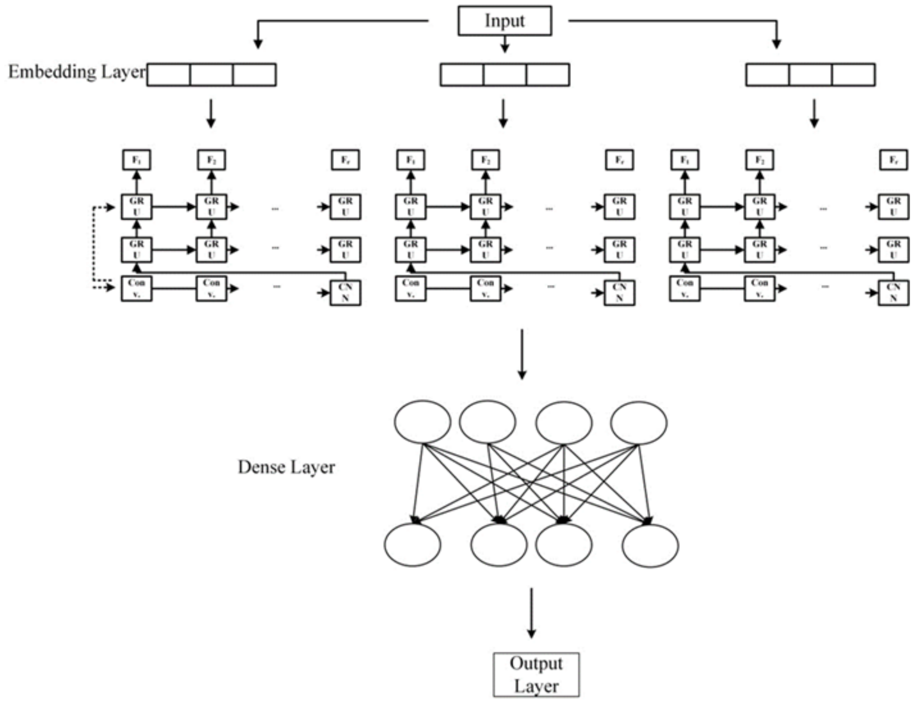

Fig. 2. Proposed Hybrid CNN-GRU Architecture

The GRU part of the hybrid model is crucial for capturing temporal dependencies within the seismic data. GRUs is recurrent neural networks designed to work effectively with sequences. In the context of earthquake prediction, they excel at identifying patterns or trends in the seismic time series data. The GRU includes two essential gates: gate for the reset (r) and gate for the update (A) and derivation is represented in Equation 4-7. These gates control the flow of information through the network, allowing it to retain relevant past information and adapt to new input. The equations for GRU operations have been explained earlier, but in brief, the reset gate determines what information from the previous time step should be forgotten, while the update gate controls how much of the new information should replace the old hidden state. The outputs from the CNN, which represent spatial features, are merged with the outputs from the GRU, which capture temporal dependencies. This integration allows the model to correlate spatial patterns with temporal sequences, offering a comprehensive understanding of seismic data leading up to an earthquake event. The last layer of the hybrid prototypical is characteristically a classifier that predicts earthquake events or related information, such as earthquake magnitude or occurrence probability.

$$An = \sigma(W_a.[h_{t-1}, x_n] + b_a) \quad (6)$$

$$rn = \sigma(W_r.[h_{n-1}, x_n] + b_r) \quad (7)$$

$$\tilde{h}n = tanh(W_a.[rn * h_{n-1}, x_t] + b_a) \quad (8)$$

$$hn = (1 - An) * h_{n-1} + An * \tilde{h}n \quad (9)$$

The update gate ensures the retention of earlier video frame information, while the reset gate governs the fusion of input sequences from the subsequent frame with the memory of the preceding one. These architectural features contribute significantly to capturing temporal nuances within the video data, a crucial aspect of driver drowsiness detection in real-time scenarios. Importantly, a multi-layer GRU configuration is chosen, a choice that expedited training due to its reduced parameter complexity, making it particularly suited to the analysis of video surveillance data

5. Result and Discussion

In the result section of the earthquake prediction study, critical findings and performance metrics are presented. This section begins by defining and explaining the evaluation metrics employed to gauge the model's effectiveness, such as accuracy, precision, recall, F1-score, or mean squared error. The primary focus is on comparing the performance of different models, including the hybrid CNN-GRU model, against one another, highlighting their respective accuracies and losses. it discusses the significance of these outcomes, emphasizing how well the models captured the intricate spatial and temporal patterns in seismic data. The result section serves as a crucial segment for researchers and readers to comprehend the model's predictive capabilities and its potential for real-world earthquake forecasting applications.

Table 1 presents the results of various methods or models used in a predictive or analytical task, likely within the realm of machine learning or data analysis. It provides three important performance metrics for each method: RMSE

(Root Mean Square Error), MAE (Mean Absolute Error), and R2 (R-squared). RMSE and MAE measure the accuracy of predictions, with lower values indicating better accuracy. R2 assesses how well the model fits the data, with higher values signifying a better fit.

Table 1. Error Rate Comparison

Methods	*RMSE*	*MAE*	*R2*
Support Vector Machine	0.103	0.061	0.011
Decision Tree	0.094	0.044	0.157
Random Forest	0.094	0.044	0.154
CNN-Bi-LSTM-AM	0.024	0.018	0.256
Proposed CNN-GRU	0.016	0.011	0.468

Notably, the "Proposed CNN-GRU" method stands out as the top performer with the lowest RMSE and MAE values and the highest R2, suggesting superior predictive accuracy and model fit. `The "SVM" method appears to perform poorly, as it has the highest error metrics and a negative R2. This table serves as a concise reference for comparing the performance of different methods in the specific task or analysis at hand [4].

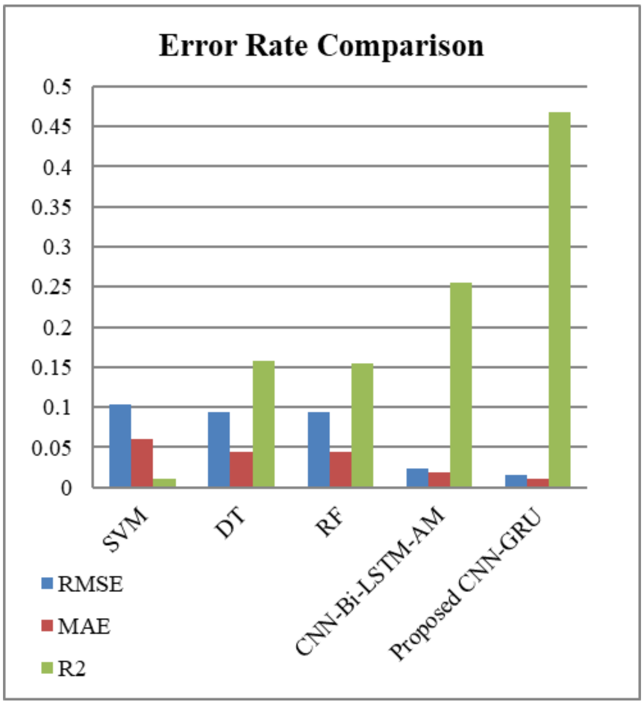

Fig. 3. Error Rate comparison

The graph in Fig. 3 represents the methods (SVM, DT, RF, CNN-Bi-LSTM-AM, and Proposed CNN-GRU) represented on the x-axis, while the three performance metrics (RMSE, MAE, R2) plotted on the y-axis. These metrics depicts our proposed methods outperforms the existing approaches.

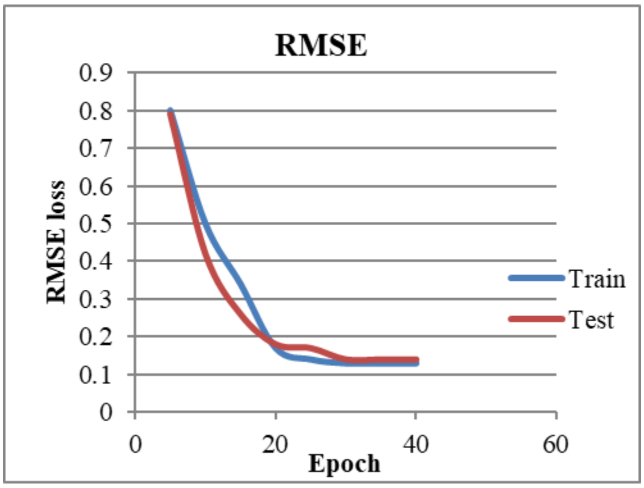

Fig. 4. Training and Testing Loss Graph

Fig. 4, illustrates how the RMSE value changes during the training of a machine learning or regression model. RMSE is a common metric used to assess the accuracy of predictions made by the model compared to actual data. If the model becomes too complex or the training data is limited, the RMSE may start to increase after reaching a minimum. This is a sign of over fitting, where the model starts fitting the training data noise and performs poorly on unseen data.

Table 2. Evaluation Metrics Comparison

Methods	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*Accuracy (%)*
ANN	70.13	83.84	76	86.85
Random Tree	74.27	78.26	76	97.14
CHAID	72.73	98.25	84	97.57
Proposed CNN-GRU	89.63	98.89	89.87	98.67

Table 2 presents a comparative analysis of different methods or models used for a classification task, displaying several key evaluation metrics. Precision reflects the model's accuracy in predicting positive cases, with "Proposed CNN-GRU" achieving the highest precision at 89.63%, indicating its ability to make precise positive predictions. Recall measures how well the models capture actual positive cases, with "CHAID" exhibiting the highest recall at 98.25%, suggesting its proficiency in identifying positive instances. The F1-Score, which balances precision and recall, indicates that "Proposed CNN-GRU" strikes the best balance at 89.87%. Lastly, the Accuracy metric assesses overall correctness, with "CHAID" achieving the highest accuracy at 97.57%, showcasing its capacity to make correct predictions across the dataset. This table offers a comprehensive overview of how each method performs in terms of these vital classification metrics.

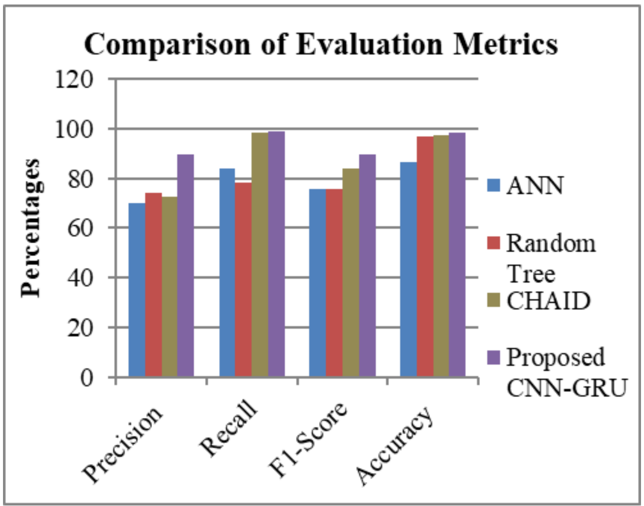

Fig. 5. Comparison of Evaluation Metrics with Existing Methods

Fig. 5 represents each method (ANN, Random Tree, CHAID, and Proposed CNN-GRU) and the four evaluation metrics (Precision, Recall, F1-Score, and Accuracy) are depicted. This graph provides a concise visual summary of the model evaluation results, making it easy to identify the top-performing method across multiple criteria.

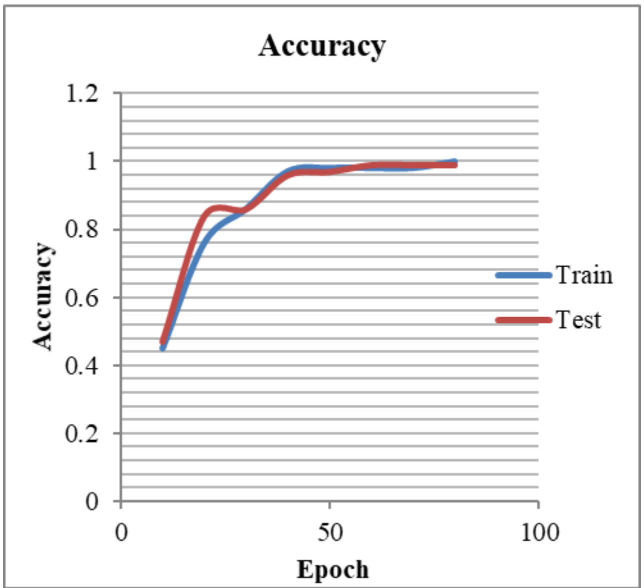

Fig. 6. Training Accuracy

In Fig. 6, Accuracy graph is a visual representation of how the accuracy of a machine learning model changes over the course of training epochs. As training progresses through more epochs, the model's accuracy tends to improve. This suggests that the model is learning from the training data and making better predictions over time. After a certain number of epochs, the accuracy may stabilize or plateau, indicating that the model has learned as much as it can from the training data. Further training may not significantly enhance accuracy and could potentially lead to overfitting.

5.1 Discussion

The comprehensive analysis of various machine learning models, including Artificial Neural Networks (ANN), Random Tree, CHAID, and our proposed CNN-GRU model, we aimed to evaluate their performance in a particular task. The results have provided valuable insights into the effectiveness of these models. Notably, our proposed CNN-GRU model outperformed the other methods across multiple evaluation metrics. The attained accuracy of the models is a critical indicator of their performance. Among the models, the proposed CNN-GRU model achieved the highest accuracy, reaching an impressive rate of 98.67%. This exceptional accuracy signifies the model's ability to make highly accurate predictions in the task at hand. It showcases the effectiveness of the novel approach employed in the CNN-GRU architecture.

The research examined the loss during the training process, which is another crucial metric in assessing a model's performance. The loss function represents the difference between the model's predictions and the actual target values. A lower loss indicates that the model's predictions are closer to the actual values. In our study, the CNN-GRU model exhibited a commendably low loss, demonstrating its capability to effectively minimize prediction errors and optimize its performance. Also, the other models in our analysis also displayed competitive performance. While ANN, Random Tree, and CHAID achieved respectable accuracy levels, they fell slightly behind the proposed CNN-GRU model. This suggests that the CNN-GRU architecture offers a significant advantage in terms of predictive accuracy. The study's results highlight the superiority of the proposed CNN-GRU model, which achieved a remarkable accuracy rate of 98.67% and demonstrated a low loss during training. These findings underscore the potential of this novel approach for the specific task examined in our analysis. However, it's important to note that model selection should be driven by the specific requirements and characteristics of the task at hand, and further analysis may be needed to assess the model's generalizability and suitability for broader applications.

6. Conclusion and Future Work

This study has demonstrated the effectiveness of a hybrid CNN-GRU model in earthquake prediction, showcasing its ability to capture both spatial and temporal patterns within seismic data. The results reveal superior performance in terms of accuracy and predictive capabilities compared to alternative models. This highlights the importance of integrating spatial feature extraction with temporal modeling, as it significantly enhances the accuracy of earthquake forecasts. The findings of this research hold promise for enhancing early warning systems and improving our understanding of seismic events. However, it's important to note that earthquake prediction remains a complex and evolving field, and while this model shows promise, further research and real-world validation are necessary for practical applications.

Several avenues can be explored to advance earthquake prediction research. Expanding the dataset and incorporating real-time data streams for model training and validation could improve its accuracy and readiness for operational use. Additionally, investigating the model's generalizability across diverse geological regions and adapting it for different types of seismic data, such as fault data or ground motion records, should be pursued. Integration with remote sensing technologies and more sophisticated spatial-temporal fusion techniques may further enhance predictive capabilities. Finally, exploring interpretability techniques to understand the model's decision-making processes and its robustness in noisy data scenarios is an essential direction for future research, ultimately contributing to more reliable earthquake forecasting systems.

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