Advancements in seismic data collection and analysis through machine learning

Sujata Kulkarni[1], Malay Phadke[1], Ashwini Sawant[2], Neel Patel[1], Om Patil[1]
[1]Department of Electronics and Telecommunication Engineering, Sardar Patel Institute of Technology, Andheri, India
[2]Department of Electronics and Telecommunication Engineering, Vivekanand Education Society's Institute of Technology, Chembur, India

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ABSTRACT

The evolution of seismic data collection has been driven by the need for stations to capture large volumes of high-frequency signals continuously. These signals typically contain both seismic and non-seismic information. Previous research converted SEED data into CSV format and used principal component analysis (PCA) for feature extraction from the seismic dataset. Machine learning models were then employed, showing an improvement in identifying seismic and non-seismic events. This paper focuses on applying deep learning methods, specifically deep neural networks (DNN) and a hybrid model combining long short-term memory (LSTM) networks with DNN (LSTM+DNN). The proposed deep learning models demonstrate a notable improvement over traditional machine learning technique. Experimental results show a test accuracy of 99.24% using deep learning, compared to an average of 97.80% achieved with machine learning models, indicating a 1.46% enhancement in detection accuracy. This underscores the potential of deep learning in accurately detecting seismic events in real-time monitoring systems.

Corresponding Author:

Sujata Kulkarni
Department of Electronics and Telecommunication Engineering, Sardar Patel Institute of Technology
Andheri, India
Email: sujata_kulkarni@spit.ac.in

1. INTRODUCTION

Early detection of earthquakes is essential for reducing damage and saving lives [1]. Earthquakes are typically caused by plate tectonics and the sudden release of elastic energy stored in geological faults, resulting in the shaking of the Earth's surface. This energy release generates seismic waves, and the magnitude of an earthquake is proportional to the logarithm of the energy released. Technological developments have greatly increased the knowledge of the interior structure and dynamic processes of the Earth. One example is the better recording of seismic waves using sensitive sensors such as seismographs. These developments are essential to increasing the capacity to anticipate and lessen the effects of earthquakes, which are among the most [2].

Managing the large volumes of data generated by seismic stations, which continually record signals at high sample frequencies, is challenging but crucial for understanding seismic activity. Seismographs, derived from ground motion data recorded by accelerographs, are used by researchers and seismologists to determine key parameters such as wavelength, frequency, magnitude, and timing of seismic signals [3], [4]. Identifying the primary (P-wave) and secondary (S-wave) waves in these signals is crucial as they frequently contain both seismic and non-seismic data as shown in Figure 1. S-waves follow P-waves during an earthquake, which are the fastest seismic waves but are hard to detect because of their low frequency [5].

Furthermore, as illustrated in Figure 2, three-component seismogram data that record ground motion in vertical, north-south, and east-west directions, along with information from Love and Rayleigh waves [6], offer a full picture of seismic occurrences. The understanding of seismic activity and the capacity to identify and respond to earthquakes will both benefit from this thorough examination.

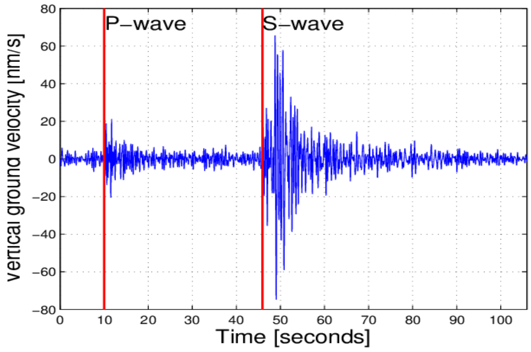


Figure 1. Earthquake with P-wave and S-wave arrivals [7]

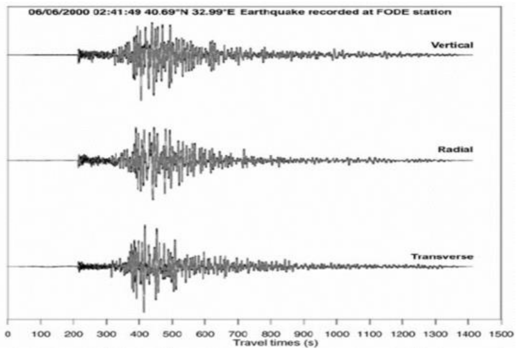


Figure 2. Three-component seismogram records ground motion in three perpendicular directions

The management of diverse and enormous amounts of seismic data has been greatly improved by the development of improved seismic data collection techniques. With these methods, there is no longer any need for continuous storing and more effective data processing because each seismic signal is handled independently. In order to provide a complete dataset with trustworthy characteristics like frequency, amplitude, and duration, seismic events are usually detected at each station using energy detectors. The raw data is then translated into CSV format [8]. To further optimize performance, dimensionality reduction techniques are applied, leading to better computing efficiency. Models such as logistic regression and decision trees have shown promising results, as indicated by precision, recall, and F1 scores. Practical applications of these methods [9] have been demonstrated with data from single sensors and sensor networks near Basavakalyan, Karnataka, yielding lower false alarm rates and highlighting their effectiveness in real-world scenarios.

Deep neural networks (DNNs) are a vital machine learning technique with significant applications in various industries [10], including seismology. Deep learning detects significant characteristics from unlabeled data more successfully than other machine learning techniques by working directly with raw data without the requirement for preparation. DNNs have been suggested in seismology for applications including lithology prediction, seismic data inversion, and earthquake detection [11]. The integration of machine learning into earthquake seismology has extended to areas like ground motion prediction, seismicity analysis, earthquake catalog development, and analyzing geodetic data related to crustal deformation [12]. Major studies have highlighted the potential of machine learning to advance seismic research, particularly through clustering analysis and detecting tectonic signals in geodetic data. These advancements demonstrate the growing importance of DNNs in enhancing the knowledge and prediction of seismic events.

The STA/LTA method [13], commonly used for monitoring energy ratios in seismic data, is effective but has limitations in precision and can be susceptible to interference, particularly in predicting shear wave arrival times. Fault Density was determined using Kernel Density Estimation and Bivariate Moran's I in order to enhance earthquake detection. It was then compared to other parameters using a variety of performance criteria, including accuracy, sensitivity, and specificity [14]. When combined with SVM and DNN models, this parameter performed very well for earthquakes with a high magnitude. Additionally, the earthquake situation learning system (ESLS), a cloud-based server using YOLO for object detection [15], achieved an average service time of 0.8 seconds and a 96% accuracy in identifying hazardous items.

Recurrent neural network (RNN) units, which capture the intrinsic temporal properties of seismic data, are employed in this study [1] to construct an efficient deep neural network-based earthquake detector and predictor. Like ANN models, the LSTM model performs well for small to medium-sized earthquakes but has trouble with large-scale occurrences. Two hybrid machine learning models (FPA-ELM and FPA-LS-SVM) were presented [16] to improve prediction accuracy; the latter model demonstrated superior accuracy in predicting earthquake magnitudes over a fifteen-day period. The research also examines machine learning algorithms such as SVM and Random Forest [17], pointing out that the ANN approach had the best prediction accuracy of 96.27% [18]. Prediction accuracy was further increased by using long short-term memory (LSTM) networks to comprehend the spatiotemporal relationships between earthquakes, particularly when utilizing two-dimensional information [19]. In addition, a technique known as PR-KNN was presented [20] to efficiently predict aftershocks with magnitudes of 4.0 or above by fusing Polynomial Regression and K-NN models. Long short-term memory (LSTM) networks were developed to overcome the shortcomings of RNNs. These networks have memory cells with input, forget, and output gates that aid in the management of long-term dependencies [21].

Previous research into categorizing seismic events has encountered multiple restrictions. Some people depended on handcrafted feature sets, possibly overlooking crucial seismic signal traits [22]. Conventional machine learning techniques like SVM or decision trees had difficulty capturing the time-related features of seismic signals, resulting in omitting important temporal data [23]. Moreover, high-dimensional datasets frequently led to over fitting, decreasing the ability to generalize [24]. Certain studies strongly emphasized precision as a measure of performance, which may be deceptive in datasets that are not evenly distributed [25].

The proposed approach is used principal component analysis (PCA) to reduce dimensionality and prevent over fitting while retaining essential seismic features. Various machine learning models, including logistic regression, Naive Bayes, SVM, decision trees, and random forests, were assessed, along with deep learning models like feed-forward neural networks and LSTM. LSTM networks were particularly effective in capturing temporal seismic patterns. Evaluation metrics such as precision, recall, F1-score, and ROC AUC were used, while cross-validation, early stopping, and learning rate adjustments were employed to improve generalization. Section 2 covers the methodology and PCA, Section 3 details model evaluation, and Sections 4–6 present the conclusion, references, and acknowledgments.

2. METHOD

2.1. Dataset outline

The data is meticulously collected from the school of earth sciences at Swami Ramanand Teerth Marathwada University in Nanded, Maharashtra, India, as well as from different stations such as BVSK and CUKG. This experimental data comes from wideband seismic signals collected by Trillium 120QA broadband seismological sensors strategically placed close to Basavakalyan and the central University of Karnataka. These advanced sensors can operate efficiently at a frequency of 100 samples per second, and possess a remarkable responsiveness of 2000 V/m/s. Every sensor follows a standardized recording cycle that lasts for 2 minutes.

The dataset spans a comprehensive five-hour period on October 12, 2021, meticulously segmented into one-hour intervals and sampled at a rate of 100 Hz. Additionally, a contrasting non-seismic or noise signal was recorded from 0:00 to 4:59:59 on July 9, 2021, as vividly illustrated in Figure 3 and Figure 4. The unique characteristics of signals recorded at each station are methodically analyzed to enrich the dataset, facilitating robust anomaly detection and precise identification of seismic events.

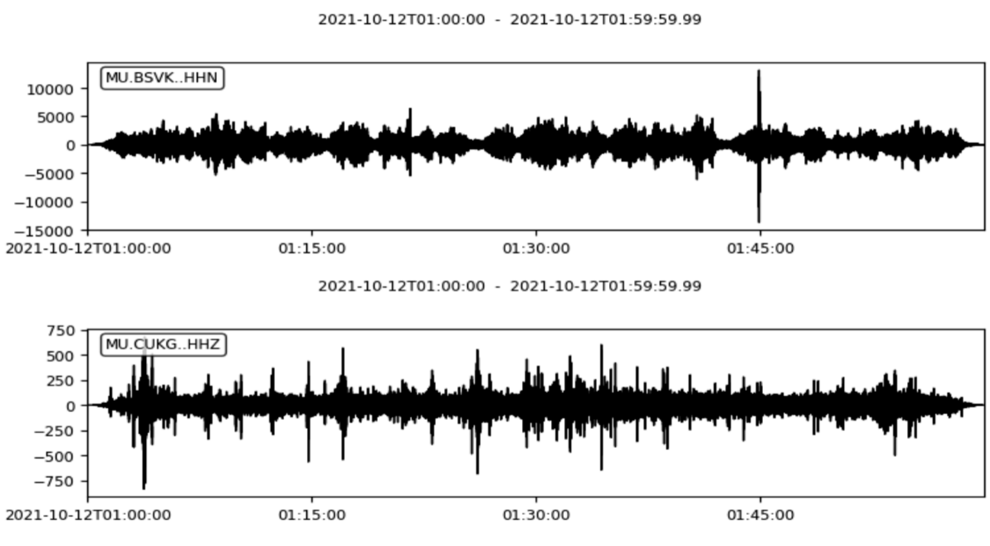


Figure 3. Dataset from BVSK & CUKG sensor network before earthquake dated 12-10-2021

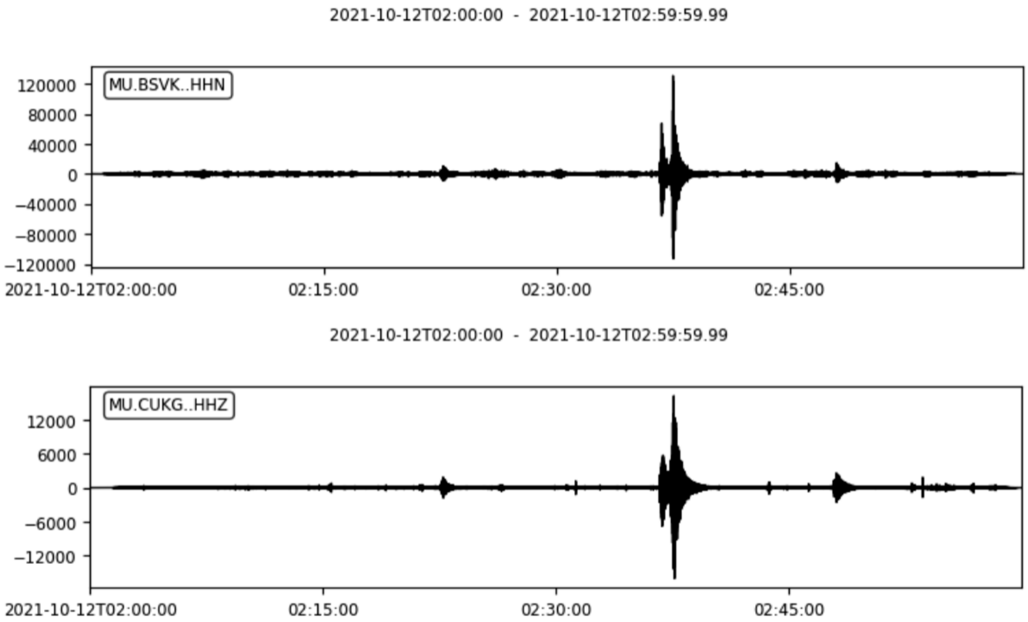


Figure 4. Dataset from BSVK & CUKG sensor network of earthquake dated 12-10-2021

Of particular note are two significant seismic occurrences recorded by the institute: an earthquake measuring 3.6 magnitude at 2:36 a.m. and another measuring 2.8 magnitude at 2:47 a.m., detailed comprehensively in Table 1. This dataset not only enhances our understanding of seismic activity but also serves as a valuable resource for advancing seismic research and monitoring capabilities. Hybrid dataset - Random selections of the data points are made from the proposed dataset to create the hybrid dataset, which includes data from various sensors such as PBA, SHL, MNC, and KBL, as well as a mixture of random samples.

Table 1. The seismic event specifies (Stations BSVK and CUKG)

Origin time	Station	Latitude	Longitude	Depth	Mag
2021-10-1202:36:27UTC	BSVKCUKG	17.36	77.3	5 km	3.6
2021-10-1202:36:27UTC	BSVKCUKG	17.33	77.29	10 km	2.8

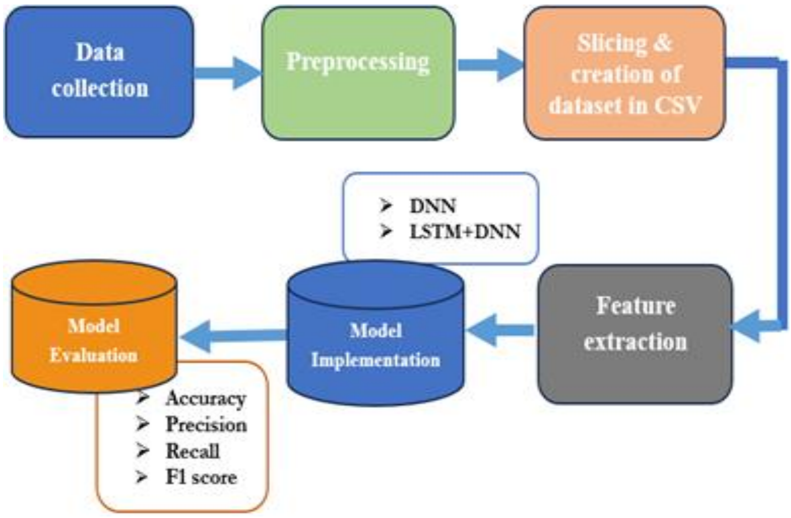
2.2. Proposed workflow

The primary objective of this study is to utilize a custom dataset containing critical features for differentiating seismic and non-seismic signals. An effective feature extraction method will be designed to rapidly and precisely identify seismic events. These features will enable the creation of a resilient model that combines LSTM and DNN for accurate signal classification.

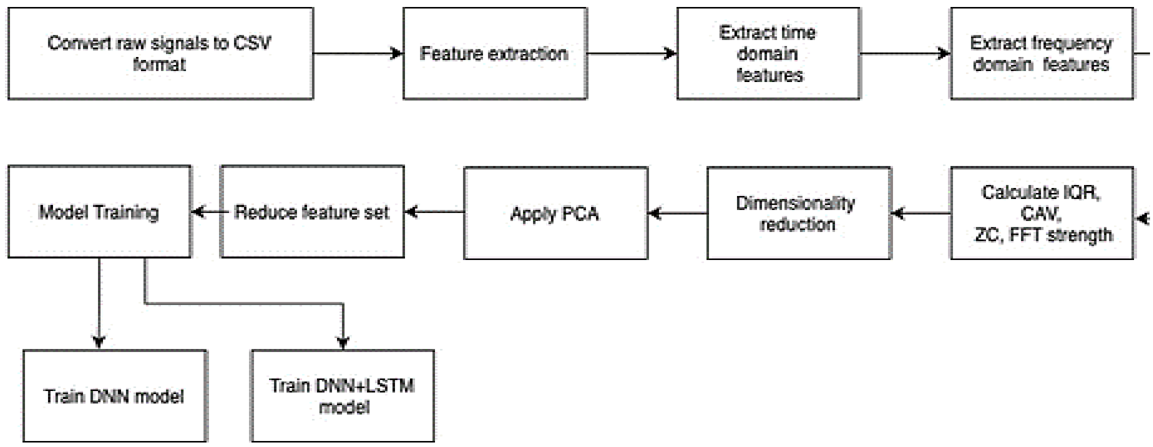
The LSTM will capture temporal dependencies in the signals, while the DNN will refine the classification process. This hybrid approach ensures improved accuracy and reliability for detecting seismic occurrences:

- The proposed workflow is illustrated in Figure 5, which provides a comprehensive overview of the methodology for identifying seismic events. The figure captures the major stages of the workflow, starting from data collection, preprocessing, feature extraction, model implementation, and concluding with model evaluation. It emphasizes the sequential flow of processes needed to develop an optimal deep learning model for distinguishing seismic from non-seismic signals.
- Figure 5(a) presents the block diagram, outlining the major steps: data collection, preprocessing, slicing and creating the dataset, feature extraction, model implementation using DNN or LSTM+DNN, and model evaluation based on metrics like accuracy, precision, recall, and F1 score. This diagram gives a high-level view of the system's workflow.
- Figure 5(b) provides the detailed flow graph for feature extraction and model training. It explains how raw signals are converted into CSV format, features are extracted in the time and frequency domains, and dimensionality reduction techniques like PCA are applied. The reduced feature set is then used to train the DNN and LSTM+DNN models, ensuring improved efficiency and accuracy. Together, these sub-figures

give a complete representation of the proposed workflow.
- Output: Optimal deep learning model for identifying real occurrences, and detection of seismic events. The seismic signals are divided into 15-second intervals and arranged in a structured table or CSV format to create a dataset. This data collection records important details from seismic signals, specifically emphasizing on amplitude and frequency.



(a)



(b)

Figure 5. Details about proposed work (a) block diagram and (b) flow graph

The characteristics are examined in terms of X, Y, and Z components. Different computations based on the time domain, including the interquartile range (IQR), cumulative absolute velocity (CAV), and the number of zero crossings (ZC), are established. Furthermore, suggested new assessment features include activation threshold, variability measure, and FFT strength and frequency.

2.3. Extraction of Features

The seismogram variables present in the dataset are applicable for identifying and forecasting real earthquakes. The computed dataset is thorough because it includes derived features from features of amplitude, frequency, and time. After applying preprocessing methods for deep learning, the total number of features was 17. The PCA, a dimension reduction technique is utilized to select the salient features from the deep learning model because it was too time-consuming to run a model with so many characteristics.

PCA is a statistical technique that uses an orthogonal transformation to change a group of correlated variables into a fresh set of uncorrelated variables. Typically, the count of principal components is equal to or fewer than the initial variables**.** PCA is useful for reducing the dataset's dimensionality while preserving most of the data's variance, which is important for efficient computation and enhanced model performance.

Components with higher eigenvalues compared to the average eigenvalues of all components in the analysis are recognized as the most critical characteristics [5]. In the proposed research, PCA is effectively utilized to generate a 3-feature vector from the dataset, decreasing the computational burden while maintaining vital information. Figure 6 displays the closely related characteristics that were effectively obtained from the combined dataset of 18,548 samples. Figure 7 showcases the main characteristic vector, which is then inputted into deep learning models for additional processing and prediction purposes.

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Raw Eigenvalues:
 [8.47169998 4.34915698 1.99211653 1.0079653  0.2736474  0.26967107
 0.03437816 0.0491924  0.06551734 0.10754679 0.15674599 0.17237991]
Percentage of Variance Explained by Each Component:
 [0.49980478 0.25658716 0.11752888 0.05946692 0.01614437 0.01590978
 0.00202821 0.0029022  0.00386533 0.00634494 0.00924754 0.0101699 ]
Mean eigen value 1.4125014878686502
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Figure 6. Correlated features

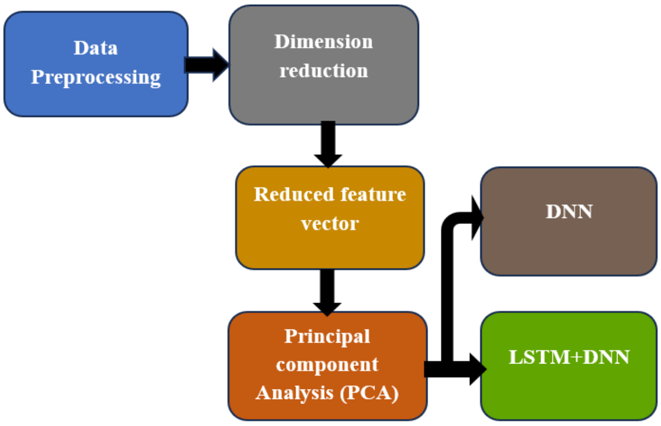

Figure 7. Extracting features and analyzing those using deep learning models

2.4. Model architecture

2.4.1. DNN model architecture

A DNN intended for binary classification tasks is set up using the architecture depicted in Figure 8. This network consists of dropout layers to reduce over fitting and several fully linked (dense) layers with ReLU activation functions. An input layer, two hidden layers with 128 neurons each, a third hidden layer with 32 neurons, and a final output layer with a sigmoid activation to produce binary results are all included. The model is assembled using the binary cross-entropy loss function and the Adam optimizer for training. Early stopping and learning rate decrease on plateau callbacks are used in its training to improve efficiency and prevent over fitting.

2.4.2. Combination of LSTM and DNN model architecture

A DNN intended for binary classification tasks is set up using the architecture depicted in Figure 9. This network consists of dropout layers to reduce over fitting and several fully linked (dense) layers with ReLU activation functions. An input layer, two hidden layers with 128 neurons each, a third hidden layer with 32 neurons, and a final output layer with a sigmoid activation to produce binary results are all included. The model is assembled using the binary cross-entropy loss function and the Adam optimizer for training. Early stopping and learning rate decrease on plateau callbacks are used in its training to improve efficiency and prevent over fitting.

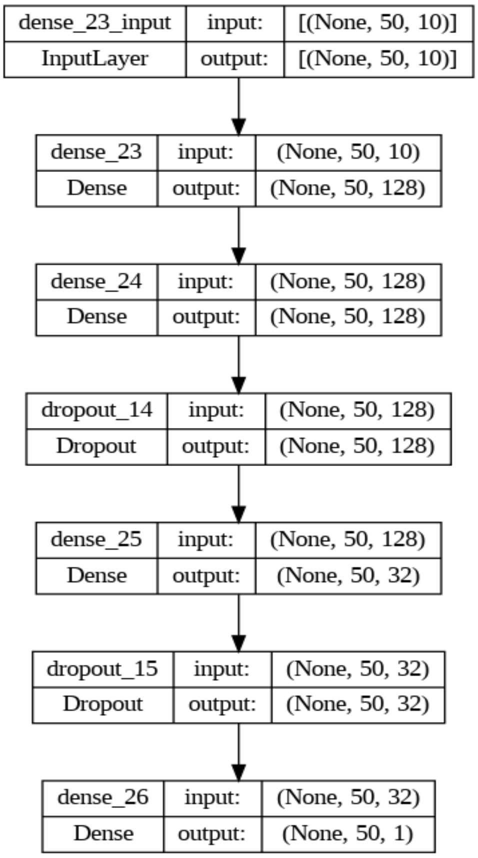

Figure 8. Architecture of the DNN Model

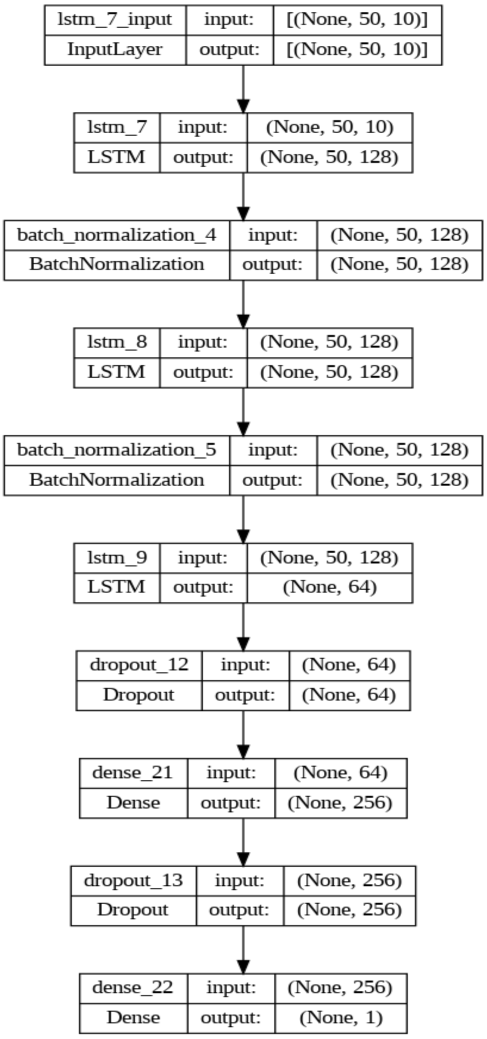

Figure 9. Architecture of the LSTM+DNN Model

3. RESULTS AND DISCUSSION

The model's effectiveness is evaluated by utilizing the hybrid dataset which includes both the proposed sensors and additional sensors. 80% of datasets are allocated for training and one-fifth of the amount is designated for testing. Both models, DNN and LSTM+DNN, are tested on the dataset through experimentation. Figure 10 and Figure 11 show the example receive operation. Receiver operating characteristic (ROC) curves of both models derived from suggested test data. Figure 12 and Figure 13 show the precision-recall curve for the models according to suggested test data. ROC analysis was used to determine the true positive rate compared to the false positive rate for each model. Assessments on the suggested test dataset show that all models portray satisfactory accuracy levels.

Table 2 highlights the performance metrics of two models, DNN and a hybrid LSTM+DNN, in terms of accuracy, precision, recall, F1 score, and AUC. The DNN model demonstrates superior accuracy at 99.24%, with a precision of 99.54% and an F1 score of 98.69%, indicating strong predictive capabilities across multiple metrics. Although slightly lower, the LSTM+DNN hybrid achieves an accuracy of 99.09%, maintaining competitive precision (99.00%) and recall (97.85%), showcasing its potential for complex pattern recognition tasks.

Table 3 provides the confusion matrix for the hybrid dataset, detailing True Positives, True Negatives, False Positives, and False Negatives. These values offer insights into the model's classification reliability and error distribution, allowing further evaluation of its strengths and areas for improvement. Analyzing these metrics is crucial for fine-tuning the models and understanding their practical implications in real-world scenarios.

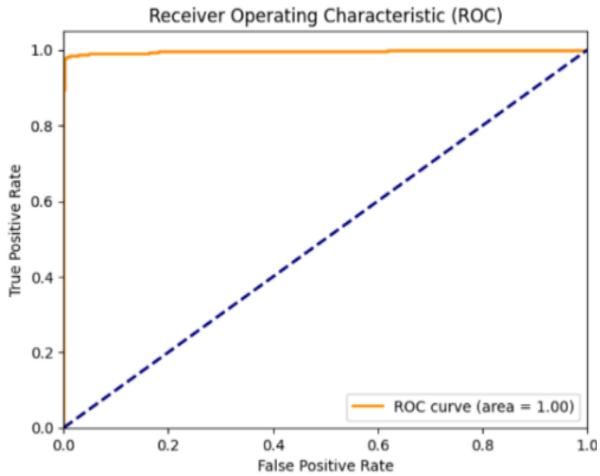

Figure 10. DNN ROC

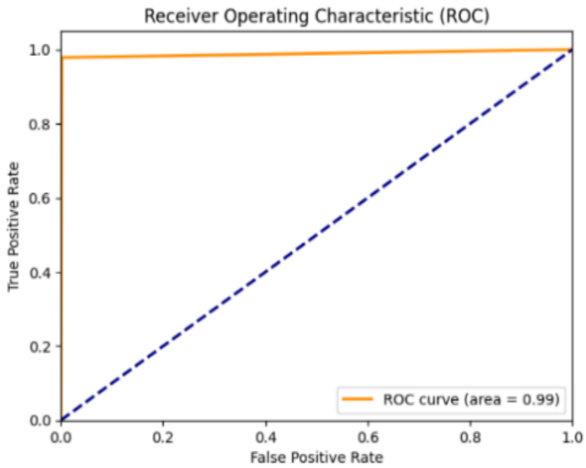

Figure 11. LSTM ROC

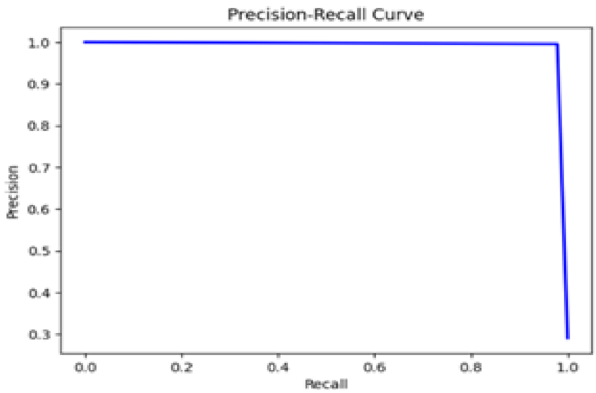

Figure 12. DNN PRC

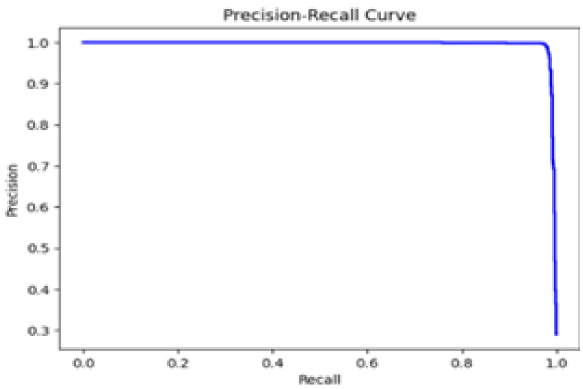

Figure 13. LSTM PRC

Table 2. Performance metrics of different models

Model	Accuracy	Precision	Recall	F1	AUC
DNN	0.9924	0.9954	0.9785	0.9869	0.9884
LSTM+DNN	0.990	0.99	0.9785	0.9842	0.9873

Table 3. Confusion matrix of different models

Model	TP	TN	FP	FN
DNN	2732	1097	5	24
LSTM+	2726	1097	11	24

3.1. Results of DNN model

The model's accuracy is approximately 99.24%, meaning that nearly all predictions are correct. The precision is very high at around 99.54%, indicating that almost all positive predictions are accurate, with minimal false positives. The recall rate is about 97.85%, demonstrating that the model effectively recognizes most true positive cases, with few false negatives. Moreover, the F1 score, which strikes a balance between recall and precision, is approximately 98.67%. This high F1 score signifies a well-balanced performance between precision and recall, ensuring the model is reliable in both identifying positive instances and minimizing false positives.

3.2. Results of combination of LSTM and DNN model

The comparison of the proposed LSTM and DNN hybrid model with previous approaches, as presented in Table 4, highlights its significant advantages in performance metrics. The test accuracy of the proposed deep learning approach is 99.24%, which is an improvement of 1.46% over the best-performing machine learning methods outlined in the study by Kulkarni *et al.* [8]. Their methods, which include Logistic Regression (LR), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM), achieve a maximum accuracy of 97.80%. This improvement underscores the effectiveness of deep learning methods in handling complex datasets and extracting meaningful patterns.

Similarly, the F1 score of the proposed approach, at 98.67%, outperforms the previous models, which achieved an F1 score of 96.00%. This indicates that the LSTM and DNN hybrid model provides a better balance between precision and recall, minimizing false positives and negatives. By leveraging the strengths of both LSTM for sequence modeling and DNN for feature extraction, the proposed approach demonstrates its capability to outperform traditional machine learning algorithms.

Table 4 provides a comprehensive comparison of these results, clearly showcasing the benefits of using deep learning techniques for improving classification performance. These findings reaffirm the proposed model's potential to achieve more reliable and accurate predictions, making it a better fit for applications that demand high precision and recall.

Table 4. Comparison with previous work

Study	Machine learning methods	Deep learning methods	Test accuracy	F1 score
Proposed approach	-	DNN & LSTM	0.9924	0.9867
Kulkarni *et al.* [8]	LR, NB, DT, RF, SVM	-	0.9780	0.96

4. CONCLUSION

Deep learning techniques, such as DNN and LSTM models, have proven highly effective in analyzing seismic signals and improving earthquake detection accuracy. This is supported by their high accuracy and reduced false alarm rates, making them ideal for real-time monitoring. These models significantly enhance the ability to distinguish between genuine seismic events and human-caused anomalies, optimizing computational efficiency while ensuring rapid and accurate detection. This improvement is crucial for monitoring earthquake-prone regions. The real-time accuracy of these models can greatly enhance early warning systems, reducing false alarms and providing timely detection, which strengthens disaster preparedness, ultimately saving lives and minimizing infrastructure damage. A key limitation of this research is that the model detects earthquakes based on seismic signals rather than predicting them in advance, lacking the lead time for preventive measures. Additionally, the use of a limited dataset from a few seismic stations may limit the model's applicability to other regions with varying seismic patterns. Incorporating predictive analysis could enable future models to offer both detection and prediction, significantly enhancing disaster preparedness. Utilizing cloud computing and global seismic networks, the system could monitor worldwide seismic activity and support global earthquake detection efforts.

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BIOGRAPHIES OF AUTHORS

Prof. Dr. Sujata Kulkarni holds Ph.D. in Electronics Engineering having work experience of more than 5 years in the industry. She has been in the teaching profession for over 16 years, of which she has been associated as a Professor with Bhartiya Vidya Bhavans' Sardar Patel Institute of Technology, Mumbai University for more than 5 years. Her areas of interest are image processing, machine learning, deep learning, and its applications. She can be contacted at email: sujata_kulkarni@spit.ac.in.

Mr. Malay Phadke is a Final Year Electronics and Telecommunication Engineering student from Bhartiya Vidya Bhavans' Sardar Patel Institute of Technology, Areas of interest-computer vision, machine learning and robotics. He can be contacted at email: malay.phadke@spit.ac.in.

Prof. Dr. Ashwini Sawant holds a Ph.D. in Electronics and Telecommunication Engineering from Mumbai University. She has over 18 years of experience in the teaching profession, including more than 12 years as a Professor at Vivekanand Education Society's Institute of Technology, affiliated with Mumbai University. Her research interests encompass biomedical image processing, machine learning, pattern recognition, and its applications. She can be contacted at email: ashwini.sawant@ves.ac.in.

Mr. Neel Patel is a Final Year Electronics and Telecommunication Engineering student from Bhartiya Vidya Bhavans' Sardar Patel Institute of Technology, areas of interest-computer vision, machine learning, and NLP. He can be contacted at email: neel.patel@spit.ac.in.

Mr. Om Patil is a Final Year Electronics and Telecommunication Engineering student from Bhartiya Vidya Bhavans' Sardar Patel Institute of Technology, areas of interest-machine learning, and natural language processing. He can be contacted at email: om.patil@spit.ac.in.