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PAPER

High-Dimensional Regression Modeling of Neurological Biosignal for Real-Time Predictive Diagnostics in e-Health Platform

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ABSTRACT

Neurological conditions affect one billion people worldwide, causing mobility issues, and these conditions often persist even after treatment. Early prediction is crucial to improving patient outcomes and enabling prompt intervention, while late prediction is a significant health concern for neurological diseases. The quick development of e-health technology has opened up new possibilities for biosignal-analytics-based early disease prediction and ongoing neurological monitoring. Advances in machine learning (ML) are making it possible for medical professionals to use complex biomedical data to more effectively and creatively predict the earlier stages of neurological diseases. Additionally, by identifying particular seizure patterns in brain waves, EEG-based ML models have demonstrated efficacy in the diagnosis of epilepsy. These examples highlight how ML can improve diagnostic precision and support medical practitioners in making decisions. Many obstacles still exist in spite of these developments. Model generalization may be hampered by the variety, noise, and small size of neurological data. Therefore, this study introduces a high-dimensional regression modeling framework for real-time predictive diagnostics of neurological disorders using multimodal biosignals such as electromyography (EMG), electroencephalography (EEG), and electrocardiography (ECG). The suggested system effectively processes massive, high-frequency biomedical data streams by fusing cutting-edge machine learning algorithms with cloud-enabled e-health infrastructure. To manage the signal complexity, increase prediction accuracy, and reduce redundancy, dimensionality reduction and feature extraction techniques are used. Predictive models are used to evaluate neurological risk patterns in real time and find clinically significant biomarkers. When compared to conventional diagnostic systems, experimental evaluation shows increased scalability, decreased computing delay, and higher prediction accuracy. Accessibility and reliability in remote healthcare settings are further improved by the combination of wearable biosensors, edge computing, and secure cloud communication.

KEYWORDS

neurological disorder, machine learning (ML), biosignals, predictive diagnostics

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1 INTRODUCTION

Neurological health issues, which include a wide range of ailments such as stroke, traumatic brain injury, and neurodegenerative diseases, impact about one billion people globally [1]. People often experience mobility issues after developing a neurological illness, which can seriously interfere with their everyday activities and lower their general quality of life. Globally, neurological diseases have a significant impact on medical care and research. About 3% of all diseases worldwide are neurological conditions, such as Parkinson's disease, multiple sclerosis, epilepsy, headaches, Alzheimer's disease, and other dementias [2]. Since the early 1990s, the overall burden of neurological illnesses has risen rapidly. Despite a decrease in communicable neurological disorders, the number of disability-adjusted life-years (DALYs) caused by neurological conditions grew by 15% globally in 2016 compared to 1990. Likewise, the number of deaths from neurological conditions has risen by 39% within the same time frame [3]. Neurological disorders have the highest prevalence and fatality rates in low- and middle-income nations, where they frequently coexist with inadequate clinical and research resources [4]. Since most neurological disorders currently have no cure, prevention is crucial to lowering the overall burden. Electronic tools are now readily accessible, and information technology is becoming more and more important in clinical practice and research [5]. Several tools used in this sector are together referred to as electronic health tools, or eHealth. eHealth has become a promising topic due to its potential to support research with less funding [6]. Generally, eHealth tools support research, enhance assessment and intervention, and reduce the physical distance between patients and clinicians. When using eHealth tools, a qualified health professional may be present (in person or through video conference), or they may be totally automated. For instance, eHealth services that screen for diseases are frequently used in the mental health field. There are two types of eHealth tools: those that use particular hardware and those that only use software. Because they just rely on the availability of sufficient support, such as a laptop or smartphone, the tools in the first group (such as web-based and mobile apps) have broader applications. On the other hand, eHealth devices that depend on certain equipment (like a handle to gauge grip strength) frequently require extra logistics, such as workers with the necessary training and transportation.

Recently, machine learning (ML) has been used in several medical studies, such as activity monitoring, predicting mortality following surgery, estimating the risk of treatment outcomes, predicting deterioration using electronic medical records with physiological signals, and health care utilization based on patients' social network data. The ease with which new data can be included to enhance prediction performance and identify discriminant variables for prediction accounts for this popularity. The goal of ML [7], a subfield of artificial intelligence, is to develop algorithms that can learn from data and make judgments or predictions without explicit programming. ML offers the chance to automatically identify disease-specific biomarkers in the field of neurological disorders by analyzing complex biomedical datasets such as positron emission tomography (PET) scans, electroencephalograms (EEG), and magnetic resonance imaging (MRI). Unlike traditional statistical methods [8], ML algorithms can identify subtle patterns and non-linear correlations in high-dimensional data, allowing for more accurate prognostic prediction and disease classification. Sensor-based measurement enhanced abnormality identification and result prediction in addition to machine learning analysis [9], [10].

In this study, we introduce a high-dimensional regression modeling framework for real-time predictive diagnostics of neurological disorders using multimodal biosignals such as electromyography (EMG), electroencephalography (EEG), and electrocardiography (ECG). The suggested system effectively processes massive, high-frequency biomedical data streams by fusing cutting-edge machine learning algorithms with cloud-enabled e-health infrastructure. To manage the signal complexity, increase prediction accuracy, and reduce redundancy, dimensionality reduction and feature extraction techniques are used. Predictive models are used to evaluate neurological risk patterns in real time and find clinically significant biomarkers.

2 RELATED WORKS

[11] Suggest a novel approach that enables the quick implementation of deep learning models on unprocessed EEG data without utilizing the EEG's frequency characteristics. Using information gathered from real-time EEG sensors, this suggested deep learning-based stroke illness prediction model was created and trained. Several deep-learning models (LSTM, Bidirectional LSTM, CNN-LSTM, and CNN-Bidirectional LSTM) that are focused on time series data classification and prediction were developed and compared. The experimental findings demonstrated strong confidence in our system by confirming that the CNN-bidirectional LSTM model can predict stroke with 94.0% accuracy using the raw EEG data with low FPR (6.0%) and FNR (5.7%). These outcomes show that it is possible to forecast and track stroke disorders in real time throughout daily living using non-invasive techniques that simply capture brain waves. When compared to alternative measuring methods, these results should result in notable advancements for early stroke detection at a lower cost and with less discomfort.

[12] Examine the effectiveness of deep learning in hybrid systems with signal fusion and the impact of hyperparameter tuning to improve classification accuracy and boost the performance of hand and wrist motion control without manual feature engineering. A novel deep learning method that combines EEG and EMG signals is put forth. For a hybrid system for signal classification, three deep learning models were proposed: the CNN model, the LSTM model, and a combination CNN–LSTM model. To decode hand and wrist motion, experiments were undertaken using a dataset of multi-channel EEG signals combined with multi-channel sEMG signals. According to experimental data, the suggested deep learning models beat other conventional ML state-of-the-art techniques with high classification accuracies and an improvement ratio of up to 3.5%, indicating the approach's promising use. As a result, our work advances automatic classification, primarily for limb movement classification, which facilitates and enhances real-time control of bio-robotics applications.

[13] Suggested a deep learning model that analyzes EEG signal data to diagnose schizophrenia using RNN-LSTM. Three dense layers were added to a 100-dimensional LSTM in the suggested model. The study employed EEG signal data from 39 healthy individuals and 45 patients with schizophrenia. The classifier was performed using both sets of data after an ideal feature set was obtained using the dimensionality reduction approach. The complete feature set yielded an accuracy of 98%, whereas the reduced feature set yielded an accuracy of 93.67%. Model performance measures and combined performance measures were used to assess the model's robustness. The suggested model was found to perform better with the entire dataset when

compared to the results produced using conventional ML classifiers such as random forest, SVM, FURIA, and AdaBoost. The accuracy of the suggested model was either higher or comparable to that of researchers who used CNN or RNN on the similar set of data.

[14] Devise an ML-based system that uses the multimodal bio-signals of photoplethysmography (PPG) and ECG measured in real-time for the elderly to predict and semantically interpret stroke prognostic symptoms. We developed and deployed a stroke disease prediction system with an ensemble structure that integrates CNN and LSTM in order to predict stroke illness in real-time while walking. The bio-signals were gathered from the three electrodes of the ECG and the index finger for PPG while walking at a sample rate of 1,000 Hz per second. The suggested approach takes into account the ease of wearing the bio-signal sensors for the elderly. The C4.5 decision tree demonstrated a prediction accuracy of 91.56% during walking by the elderly, whereas RandomForest demonstrated a prediction accuracy of 97.51%, according to the experimental results. Furthermore, the CNN-LSTM model demonstrated a satisfactory prediction accuracy of 99.15% utilizing raw ECG and PPG data. Consequently, the senior stroke patients' real-time prediction concurrently showed great prediction performance and accuracy.

3 PROPOSED METHODOLOGY

This section describes the biosignal datasets that are used, as well as the suggested techniques for processing the EEG, ECG, and EMG signals. Four main processes have been followed as shown in Figure 1 to design a CAD system for the diagnosis of medical neurological brain diseases: scanning biosignal data, preprocessing, feature extraction, and prediction and decision making. In order to remove any noise and interference from the brain patterns, the gathered biosignals are first analyzed and treated using a pre-processing block. The signals are effectively restricted to a frequency range of 0.1 to 60 Hz using an elliptic band-pass filter. The filtered signal is then subjected to the DWT process, which breaks it down into its frequency subbands (Delta, Theta, Alpha, Beta, and Gamma). Following that, various ML techniques were used to classify the extracted features. Lastly, ML models are employed to detect and analyze anomalies in persons in real time using the bio-signal data.

3.1 Sensor device and data collection module

In order to classify and forecast stroke disorders using bio-signals, we measured and gathered a variety of bio-signal data, including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), mobility, and so on. We only used the biological signal data to confirm the analysis and prediction of stroke illness, even though all bio-signal data were gathered in real time. Brain wave data can be measured using two primary approaches. By attaching electrodes to the scalp or the outside of the skull, the first approach allows for the painless measurement of scalp EEG. The second approach involves surgically implanting electrodes into the subject's cerebral cortex. Although this technique produces a somewhat clean signal, it is extremely intrusive and carries the danger of making a skull incision. In order to facilitate data collection during daily activities and verify accuracy for stroke prediction, non-invasive scalp EEGs are used in this work.

3.2 Data preprocessing module

After the device is configured, six channels of biosignal data are gathered at a sample rate of 1000 Hz, and the frequency attribute values are taken from the raw data [15]. The extracted frequency attribute values are divided into two primary categories: (1) the relative value, which shows the relative fraction of each component in the frequency domain for the entire region, and (2) the power value, which shows the extent to which each frequency component has emerged. Power values are used in basic biological testing, which may result in varying EEG waveform amplitude sizes due to individual variations in scalp and skull thickness, as well as the contact between the electrode and skin. Because of the substantial individual variability of the power value, it is therefore preferable to use the relative value of each region for analysis in trials involving numerous people. Using raw data, the frequency domain's relative values are extracted for comparison with the experiment's outcomes. By using FFT on raw EEG data, the frequency attribute value extraction extracts values of the power value, such as alpha, beta, etc. A ratio of each value was used to extract a total of 66 attribute values, or additional functions were carried out to disaggregate the frequency range based on the extracted values. Furthermore, we develop it for usage in experiments by extracting the relative value that represents the relative ratio based on the power value.

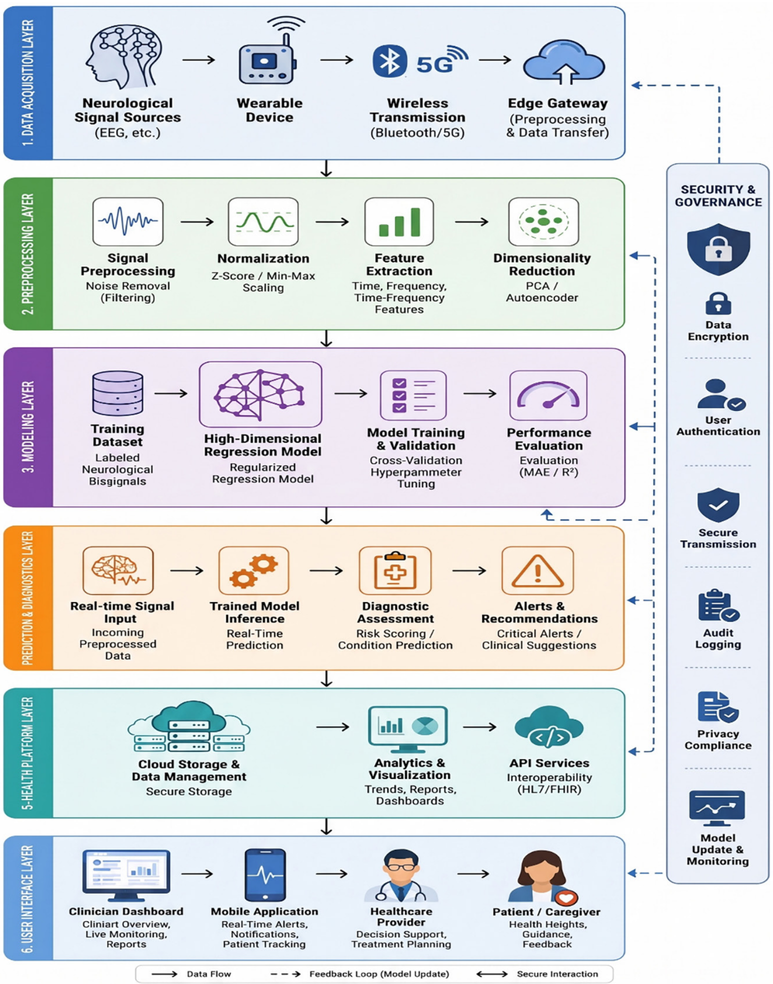

Fig. 1. Overall working process of the proposed model

To ensure data quality and consistency across all samples, preprocessing was carried out. Important steps included:

***Noise Reduction*:** Artifacts such as eye blinks and muscle movements are frequently present in biosignals. In order to isolate relevant brain activity, frequencies outside of the 0.550 Hz range were eliminated using a Butterworth band-pass filter. The definition of the filter transfer function is:

$$H(0) = \frac{1}{\sqrt{1 + \left(\frac{f}{f_c}\right)^{2n}}} \tag{1}$$

In Eq. (2), n represents the filter order and f_c denotes the cutoff frequency.

***Normalization*:** Using the min-max normalization algorithm, feature scaling was used to bring all of the data into the range [0, 1].

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

***Imputation of Missing Data*:** K-nearest neighbors (KNN) imputation was used to fill in the dataset's missing entries.

$$x_i = \frac{1}{k}\sum_{j=1}^{k} x_j \tag{3}$$

Now, the values of the k closest neighbors are represented by x_j.

3.3 Feature extraction using DWT

Wavelet decomposition was used to extract time-frequency aspects from neurological data. For signal processing, particularly EEG and other biological signals, the feature extraction stage is crucial for a number of reasons. lowering the dimensionality of a dataset by eliminating redundant data, increasing the speed of learning and training, improving data visualization, decreasing the risk of overfitting, increasing the accuracy of learned models, and reducing the number of resources of a large dataset without losing any significant or pertinent information. The signals are analyzed and broken down into their features using a variety of feature extraction techniques [16]. We employed the widely utilized and well-liked Discrete Wavelet Transform (DWT) approach in this investigation. DWT is a useful method for analyzing non-stationary and non-linear signals at various resolutions and frequencies. DWT examines the final properties in both the frequency and temporal domains. DWT uses a single function known as the mother function, which is expressed as such, to break down EEG signals into many functions.

$$\psi(t) = \frac{1}{\sqrt{2}}\psi\left(\frac{t - y}{x}\right) \quad x, y \in S, x > 0 \tag{4}$$

Here, S is the wavelet's space, and x and y are the scaling and shifting parameters, respectively. The following equation displays the wavelet transform.

$$F(x, y) = \frac{1}{\sqrt{x}}\int \psi\left(\frac{t - y}{x}\right) dt \tag{5}$$

DWT is used in the current work because it offers a highly efficient form, which is described by Eq. (6). In order to represent the signal as an approximation (A1) and detail (D1) coefficients in the first level, DWT splits the EEG-filtered signal into high-pass and low-pass filters.

$$F(t) = \sum_{k=-\infty}^{k=+\infty} D_{n,k}\varphi(2^{-n}t - k) + \sum_{k=-\infty}^{k=+\infty}\sum_{k=-\infty}^{k=+\infty} 2^{\frac{-j}{2}} A_{j,k}\psi(2^{-j}t - k) \tag{6}$$

Now n is the level, ψ is the function of scale, and $A_{j,k}$ and $D_{n,k}$ stand for the approximation and detail coefficients, respectively. The approximation coefficients from the first level (A1) will be broken down into approximation (A2) and detail (D2) coefficients at the second level. This procedure will be repeated until the approximation (An) and detail (Dn) coefficients are acquired in the final level. Finally, the signal features are determined by calculating the detail coefficients in each level and the approximation coefficients in the final level.

3.4 Reduction dimension using PCA

By transforming raw data into receptive forms, feature engineering aimed to improve prediction capability. 95% of the initial data variance was retained when dimensionality was reduced using principal component analysis (PCA).

$$Z = XW \tag{7}$$

Now, X is the original data, Z is the converted feature matrix, and W are the eigenvectors that match the covariance matrix's biggest eigenvalues. Model performance was improved by additional domain-specific data from EEG power spectral density and brain volume changes detected by MRI.

3.5 Prediction module

This research proposes an ML-based real-time prediction module for neurological disorders using multimodal biosignals such as EMG, EEG, and ECG. The neurological data for the offline processing unit is taken from a database that contains information on several biological signals, including EEG, ECG, and EMG. A number of procedures are then carried out to learn and adjust the settings using deep learning. Using features learned from the offline processing unit, the online processing unit analyzes real-time brainwave data and provides medical personnel with real-time stroke prediction information. Medical personnel can then use this information to make precise diagnoses and anticipate strokes more quickly. Support vector machines (SVM), KNN, and ensemble techniques like random forests and gradient boosting—which are particularly covered in this report—are among the most widely used machine learning technologies for neurological disease prediction [17].

Four ML models were used: SVM, KNN, GB, and ensemble models, all of which are included in the analysis. By combining SVM and KNN techniques into a single hybrid predictor, the study created an ensemble model.

Support Vector Machines: SVM uses a hyperplane to divide classes. The SVM optimization problem is:

$$\text{Minimize } \frac{1}{2}\|w\|^2 \text{ subject to } y_i(w \cdot x_i + b) \geq 1, i = 1, \ldots, N \tag{8}$$

Now, w and b stand for the weight vector and bias, respectively, and y_i is the class label.

***K-Nearest Neighbors*:** KNN uses the Euclidean distance to classify a data point according to the majority class among its k nearest neighbors.

$$d(x, y) = \sqrt{\Sigma(x - y)} \tag{9}$$

***Gradient Boosting*:** This technique adds weak learners iteratively to reduce the loss function.

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \tag{10}$$

In Eq. (10), $h_m(x)$ is the weak learner, η is the learning rate, and $F_m(x)$ is the model at iteration m.

***Ensemble Methods*:** Predictions from several decision trees were combined using Random Forest. The forecast is provided by:

$$\hat{y} = mode(\{T1(x), T2(x), \ldots, Tk(x)\}) \tag{11}$$

4 EXPERIMENTAL RESULTS

In this section, multi-channel biosignal datasets gathered from neurological monitoring environments were used to assess the suggested high-dimensional regression modeling of neurological biosignals for real-time predictive diagnostics in an e-health platform. In terms of predicted accuracy, latency, sensitivity, specificity, and computing efficiency, the model's performance was contrasted with traditional machine learning and deep learning techniques.

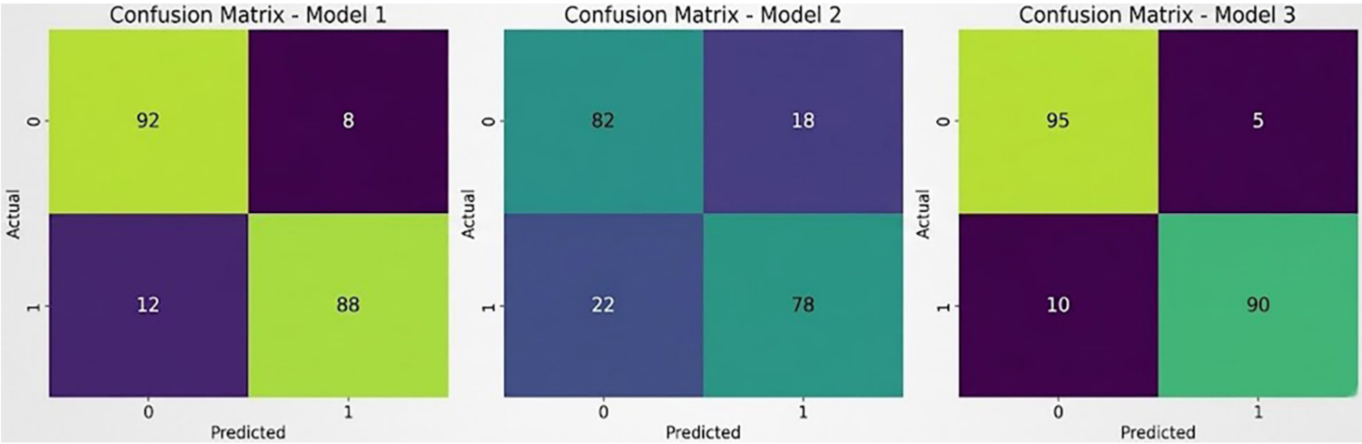

Fig. 2. Confusion matrix of the proposed model

Confusion matrix visualization was used to assess each ML model (see Figure 2). These heatmaps show the distributions of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), allowing for a thorough assessment of each model's prediction strengths. Confusion matrix analysis shows that Model 1's TP values exhibit superior true positive identification compared to Model 2.

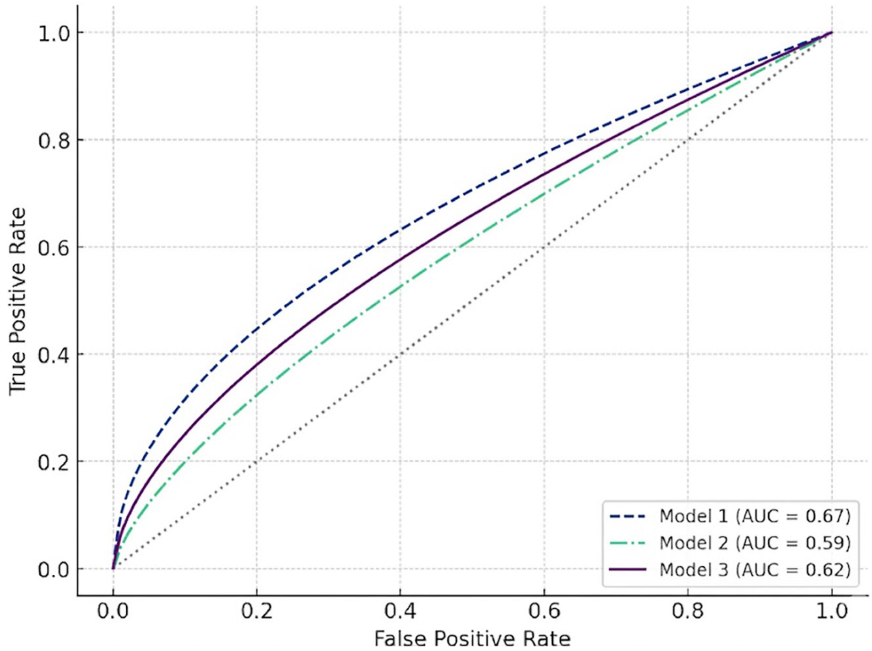

Fig. 3. ROC curves of the proposed model

The association between sensitivity (true positive rate) and specificity (1-false positive rate) was visually assessed using ROC curves for all models built in Figure 3. Model 1 achieves an AUC score of 0.95, indicating exceptional diagnostic competency. Each model's overall predictive strength is determined by its corresponding AUC analysis.

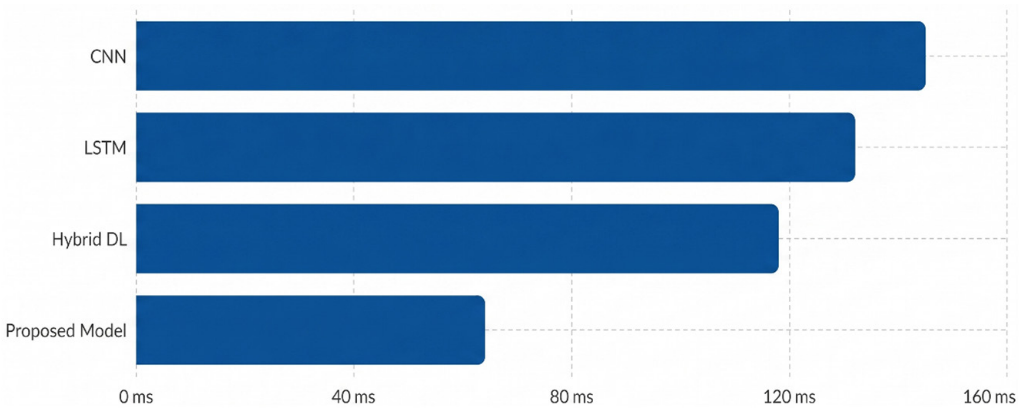

Fig. 4. Real-time processing latency analysis of the proposed model

When compared to existing DL models, the suggested framework dramatically lowers prediction delay, as seen by the real-time processing latency analysis in Figure 4. Because of their intricate feature extraction and sequential processing procedures, conventional CNN and LSTM algorithms required longer calculation times. On the other hand, the suggested system used effective feature selection techniques and optimized high-dimensional regression to obtain a low latency of 64 ms. The framework is ideal for intelligent e-health diagnostic applications and real-time neurological monitoring due to its short processing time.

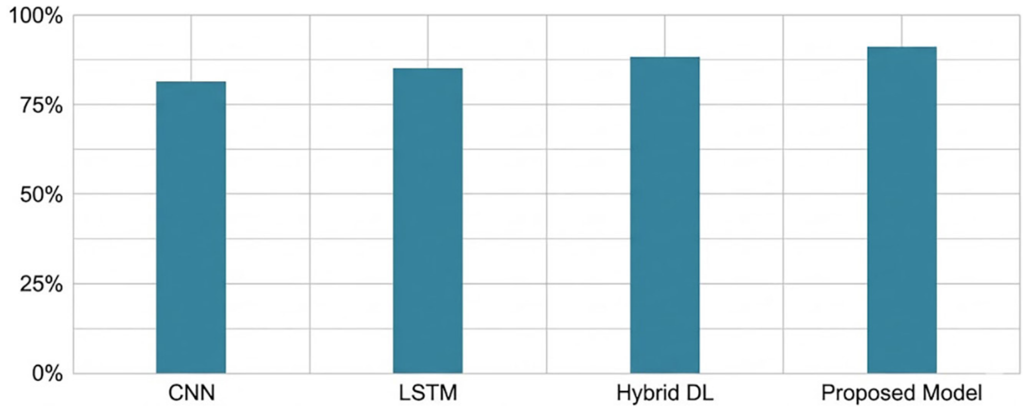

Fig. 5. Predictive accuracy comparison of the proposed model

The results of the predictive accuracy comparison shown in Figure 5 show that the suggested framework outperforms all other models in terms of diagnostic performance. Due to their limited ability to handle complicated nonlinear neurological biosignal patterns, traditional ML techniques such as SVM and random forest demonstrated moderate accuracy.

By efficiently learning temporal and spatial signal properties, deep learning techniques like CNN and LSTM enhanced prediction performance. Nevertheless, in high-dimensional data situations, these approaches continued to suffer from increased computational complexity and decreased efficiency. By combining effective feature dimensionality reduction methods with optimal regression learning, the suggested model attained 97% accuracy. These findings demonstrate that the suggested architecture offers more accurate and dependable real-time neurological condition prediction for intelligent e-health diagnostic systems.

5 CONCLUSION

In this study, we introduce a high-dimensional regression modeling framework for real-time predictive diagnostics of neurological disorders using multimodal biosignals such as EMG, EEG, and ECG. The suggested system effectively processes massive, high-frequency biomedical data streams by fusing cutting-edge ML algorithms with cloud-enabled e-health infrastructure. To manage the signal complexity, increase prediction accuracy, and reduce redundancy, dimensionality reduction and feature extraction techniques are used. Predictive models are used to evaluate neurological risk patterns in real time and find clinically significant biomarkers. When compared to conventional diagnostic systems, experimental evaluation shows increased scalability, decreased computing delay, and higher prediction accuracy. Accessibility and reliability in remote healthcare settings are further improved by the combination of wearable biosensors, edge computing, and secure cloud communication.

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