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RESEARCH ARTICLE

IOT BASED ELDER MONITORING SYSTEM USING DEEP LEARNING

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Abstract – Elderly health requires continuous monitoring to enable early detection of neurodegenerative conditions. This study positions Parkinson's disease (PD) detection as a core function of an IoT (Internet of Thing)-based elder monitoring system that collects voice and sensor data for remote analysis. Initially, voice signals are denoised using an adaptive wavelet thresholding (AWT) method, which effectively suppresses background noise and enhances the image. The proposed PD-LSTM can be integrated as the deep learning decision module in an IoT-based elder monitoring framework, enabling automated, continuous monitoring and alerting for caregivers and clinicians. Mel Frequency Cepstral Coefficients (MFCC) are used as a feature extraction technique to produce discriminant features, and a sparse autoencoder is used to extract the features of the voice signal (VS). Finally, the Bi-directional LSTM (BDLSTM) used to classify the PD such as normal, and Parkinson. The proposed PD-LSTM approach not only enhances Parkinson's detection accuracy but also forms a potential component of an IoT-enabled elder monitoring ecosystem, providing continuous and intelligent healthcare assistance. The performance of the PD-LSTM approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The PD-LSTM approach achieves a high accuracy of 99.22% for PD. The PD-LSTM improves the accuracy range of 10.47%, 3.19% and 11.85% better than ZFNet-LHO-DRN, FB-DNN, and Ma-ST-DGN respectively.

Keywords – *Parkinson disease, IoT, Elder monitoring, Voice signal, Mel Frequency Cepstral Coefficients, sparse autoencoder.*

1. INTRODUCTION

Parkinson's disease (PD), a neurodegenerative condition of the central nervous system, is distinguished by progressive degradation of dopaminergic neurons in the midbrain [1]. PD symptoms might include tremors, rigid muscles, involuntary movements (dyskinesia), speech and writing abnormalities, altered posture, restricted or slow movement (Bradykinesia), and disturbed balance [2]. With the rapid advancement of Internet of Things (IoT) technologies, healthcare monitoring systems have shifted toward continuous remote observation of elderly individuals. By combining deep learning algorithms such as PD-LSTM with IoT-enabled sensors, early detection of Parkinson's symptoms can be automated, enabling proactive elder health monitoring and intervention [2].

PD, the second most common neurological disease after Alzheimer's, (AD) affects 8-10 million people worldwide, according to estimates from the Parkinson's Foundation (PF) in the United States [5]. PD is normally diagnosed by a healthcare professional based on the patient's complaints and the findings of a post-disease neurological evaluation [6]. Despite the fact that several expensive procedures, such as radiological imaging methods like computer tomography (CT), X-ray imaging, single-photon emission CT/dopamine transporter scan, etc. [7], can only diagnose PD after it has spread throughout the brain [8, 9]. Speech, handwriting, tremor, and walking are among the physiological signs used to identify PD. Speech signals represent the non-motor symptoms of PD [10]. With the increasing availability of low-cost IoT devices and wearable sensors, continuous remote monitoring of elderly individuals has become feasible. Integrating speech and sensor data with deep learning modules (such as the PD-LSTM proposed here) enables an IoT-based elder monitoring system that can detect early signs of Parkinson's and notify caregivers or clinicians for timely intervention.

Machine learning (ML) and deep learning (DL) approaches were also applied to differentiate between individuals with PD and healthy individuals. Acoustic, spectral, and cepstral features that are taken from speech signals serve as the foundation for traditional ML techniques [11]. Recently, DL [12] techniques have produced remarkable results in PD classification tasks [13]. In classification problems, a variety of algorithms, including convolutional neural networks (CNNs), demonstrated the highest accuracy. CNNs have been used in image, audio, and video classification because of their superior ability to identify different input elements and generate the correct categorization [14].

However, the existing method was limited by the dataset used, which might not accurately capture the diversity encountered in real-world healthcare environments. The lack of external validation on distinct datasets compromises the model's robustness across a variety of demographics and recording settings. Furthermore, while the model performed well in controlled conditions, it has not yet been tested in the noisy or unstructured situations found in clinical practice, which may influence its dependability in more general diagnostic applications. To overcome this problem, the PD-LSTM approach for PD. The important contributions of the PD-LSTM approaches are as follows:

- Adaptive Wavelet Thresholding (AWT) is used to enhance the voice signal and remove background noise from human speech.
- The proposed PD-LSTM can be integrated as the deep learning decision module in an IoT-based elder monitoring framework, enabling automated, continuous monitoring and alerting for caregivers and clinicians.
- MFCC is used as a feature extraction method to produce discriminative features, while SAE extract the feature and enhances the performance of PD.
- The BDLSTM was used to improve classification accuracy and efficiently distinguish between normal and Parkinson.
- The PD-LSTM model efficiency was assessed using metrics like F1 score, specificity, recall, accuracy, and precision.

The structure of this paper and other parts of this work is as follows: Section 2 presents the literature review. The PD classification is explained in Section 3, while the findings and discussion of the PD-LSTM approaches are explained in Section 4. The conclusion and recommendations for further research are included in Section 5.

2. LITERATURE SURVEY

In this paper, researchers have proposed a number of machine learning (ML) and DL designs for PD. GCN, CNN, and RF have been used with various techniques and designs for PD in the research studies that have been proposed. Some of the research are examined in the following section.

In 2024 Saha et al. [15] proposed a PD classification using Graph Convolutional Networks (GCNs) and Euclidean distance-based graph construction. The proposed method leverages the power of GCNs to learn meaningful representations from graph-structured data while utilizing Euclidean distances to capture the similarity between patient samples. The proposed GCN-based model achieves a high classification accuracy of 97.4% on the test set, outperforming traditional ML methods such as SVM and RF.

In 2025 Shanmugam et al. [16] developed an optimized deep learning model for PD classification using VS and hand-drawn spiral images, leveraging a ZFNet-LHO-DRN. The ZFNet-LHO-DRN approach demonstrated excellent performance by achieving a premium accuracy of 89.8%.

In 2025, Valarmathi et al. [17] introduced a promising and new strategy for PD detection that integrates FB-DNN approaches and makes use of cutting-edge audio signal processing tools. Deep Neural Networks (DNN) combined with autoencoder-based feature extraction provide a dependable and simple-to-operate method for PD early detection and continuing monitoring. The best accuracy score of 96.15% was attained by the FB-DNN.

In 2025, Hasib et al. [18] developed an automated method that uses time-frequency image analysis of EEG waves to detect Parkinson's disease. The ERSP data were classified using a DL model, which allowed PD patients to be distinguished from healthy controls. The accuracy of the DL model in distinguishing between PD patients and healthy controls was 94.64%.

In 2025, Islam et al. [19] developed a hybrid approach for PD detection that combines CNN and LSTM. While LSTMs record temporal correlations, CNNs gather spatial information from the spectro-temporal components of voice data, enabling a more comprehensive analysis of how speech patterns change over time. The results indicate that the model has a remarkable 99.00% accuracy rate in identifying Parkinson's illness.

In 2025 Huo et al. [20] introduced a Ma-ST-DGN approach is a new DL model for PD identification using video dataset (VD). The approach effectively gathers temporal and geographical information from patients' movement data to better identify subtle movement abnormalities. Comprehensive testing on this clinical VD indicates the approach outperforms current sensor and vision-based algorithms for assessing PD gait, with an accuracy of 88.7%.

In 2025 Luo et al. [21] introduced a technique for distinguishing PD mice from normal mice using pressure sensor-captured footprint images. Because only one technique was utilized to develop the PD mouse model, the results cannot be extended to other PD models or situations. The results presented that when a multimodal data fusion strategy was employed instead of an image recognition method, the average classification accuracy for PD mice was 96.56%.

In the literature review, these current approaches have several limitations like difficulty in classifying PD because of low-quality signals, especially in real-world clinical settings where data variability is high. To overcome this problem, the PD-LSTM approach in PD.

3. PROPOSED METHODOLOGY

In this paper, a novel PD-LSTM approach is proposed to classify Parkinson’s disease (PD) from voice signals (VS) as part of an IoT-based elder monitoring system for remote health tracking. The voice signals are denoised using Adaptive Wavelet Transform (AWT), features are extracted using MFCC and Sparse Autoencoder (SAE), and classification is performed with a Bi-Directional LSTM (BDLSTM) to distinguish between normal and Parkinson cases, as shown in Figure 1.

3.1. Dataset

In this research, the Early Warning of Alzheimer speech database (EWA-DB) [22] was taken from the publicly available dataset for Parkinson disorder classifcation. The EWA-DB speech database includes information from three clinical groups: mild cognitive impairment, PD, AD, and a control group of healthy individuals. Speech samples were collected from each clinical group using the EWA smartphone app, which includes four language tasks: sustained vowel phonation, diadochokinetic, object and action naming, and image description. The database has a total of 1649 speakers. There are 1323 healthy controls, 87 AD patients, 175 PD, 62 people with mild cognitive impairment, and two people who have both AD and PD. We distribute audio recordings in WAV format to speakers (a total of 1003 speakers) who provided written consent.

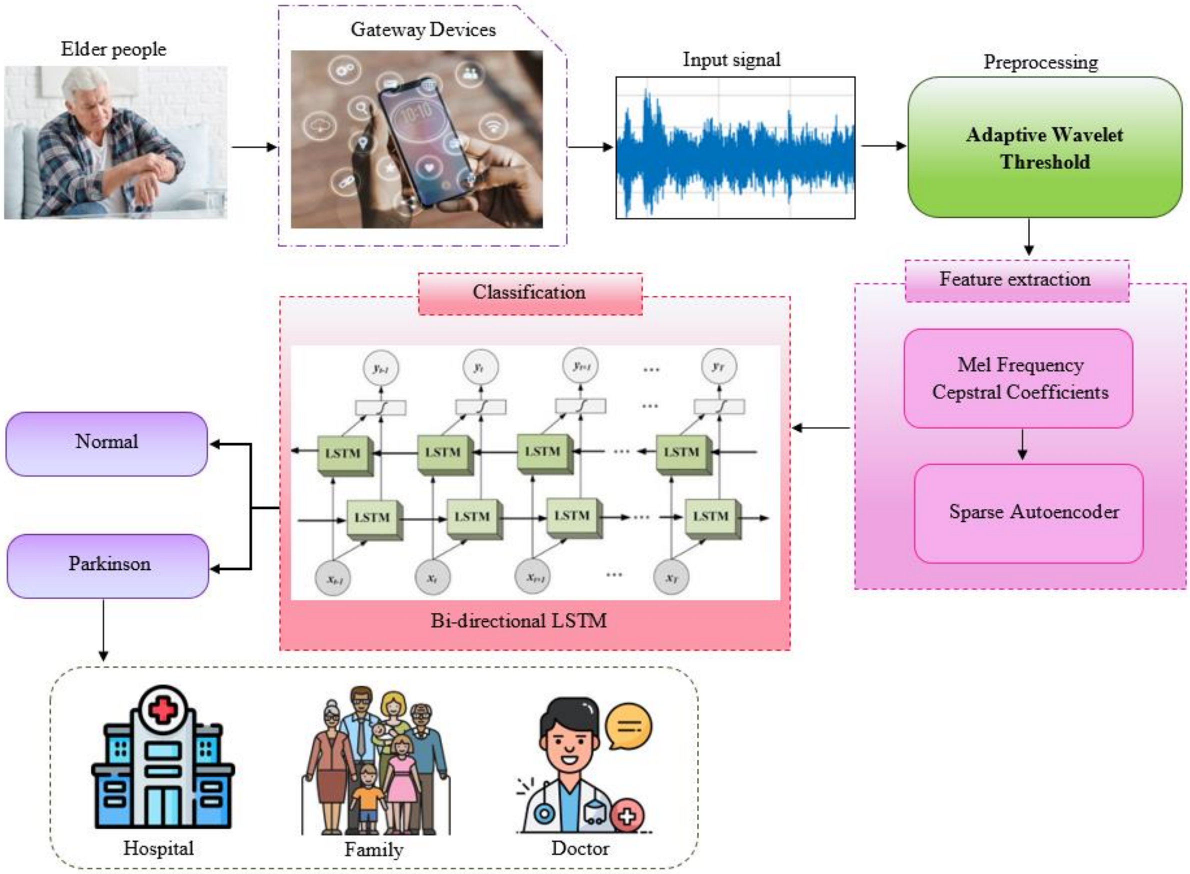

Figure 1. Overall workflow of the PD-LSTM approach

3.2. Preprocessing

Adaptive wavelet thresholding (AWT) function is employed to enhance speech quality and improve the accuracy of automated speech recognition (ASR). The utilized adaptive threshold based on the wave cleans the audio signals from the background noises, unnecessary information, and silent portions. Here, we use a direct relation approach to determine the correlation between energy and amplitude in voice signals. In this process, a direct relationship between energy and amplitude in the voice signal is considered. Since the amplitude of a wave is proportional to its energy content, it serves as an indicator of signal strength where higher amplitudes correspond to more energetic and meaningful parts of the voice signal.

$$D = A \times sin(2\pi f t) \quad (1)$$

Where, D represents the particle displacements, f is the frequency with respect to time t, and A denoted the amplitude.

3.3. IoT-Based Framework Integration

The PD-LSTM model is designed to be integrated into an IoT-based elder monitoring system. In this framework, wearable microphones and other sensors continuously collect voice and movement data from elderly users. Data can be transmitted via secure wireless links to an edge device or cloud server where the PD-LSTM module performs preprocessing (AWT), feature extraction (MFCC, SAE), and classification. Alerts or dashboards are provided to caregivers and clinicians for early intervention. This architecture supports continuous, real-time monitoring while preserving data privacy through on-edge preprocessing when required.

3.4. Feature extraction

Mel cepstral approach with Mel-frequency cepstrum coefficients (MFCC) is a variation of the cepstral method that takes advantage of the nonlinearity of human sound perception. A non-linear system is selected because the VS has a non-linear scale. The Mel filter bank tries to increase recognition performance. To calculate the Mel scale equivalent of each frequency fin Hz, use the following formula:

$$Mel(f) = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \quad (2)$$

The Sparse Autoencoder (SAE) is an axisymmetric NN with one hidden layer (HL). It is an unsupervised feature extraction method based on DNN. This network encodes the input under a HL and strives to reduce error in order to provide the best-scoring compressed vector. The fundamental principle of a typical AE model is preserved, along with a sparse penalty term and a few additional constraints to improve feature learning and latent representation extraction from input data. This network makes use of the sigmoidal activation function. The purpose of sparsity enforcement is to limit unwanted activation in the HL. The formula for the activation function is $a = sig(Wx + b)$. In this case, b is the deviation vector and W is the weight matrix.

$$\rho j = \frac{1}{n}\sum_{i=1}^{n}\left[a_j\left(x(i)\right)\right] \quad (3)$$

The Kullback-Leibler (KBL) divergence approach serves as the foundation for the punishment term, and the equation's mathematical representation is as follows:

$$KBL(\rho||\rho j) = \rho \ln\frac{\rho}{\rho j} + (1 - \rho)\ln\frac{1-\rho}{1-rho_j} \quad (4)$$

The KBL value will steadily rise with the deviation, but when it doesn't stray from ρ, the KBL divergence becomes zero. The network's loss function can be expressed as $C(W, b)$.

$$C_{sparse} = C(W, b) + \beta\sum_{j=1}^{S_2} KBL(\rho||\rho j) \quad (5)$$

where β is the weight of the sparse penalty term and S_2 is the number of neurons in the internal layer.

3.5. Classification

The Bidirectional LSTM (BDLSTM) network is a combination of BDRNN with LSTM cells. BDLSTM generates the forward hidden sequence $\vec{h}$, the backward hidden sequence $\overleftarrow{h}$, and the output sequence y by iterating the forward layer from $t = (1, \cdots, N)$ and the backward layer from $t = (N, \cdots, 1)$ (where N is the maximum length of input sequences). The output layer is then updated according to the following:

$$\vec{h}_t = S\left(W_{AF\vec{h}}AF_t + W_{\vec{h}\vec{h}}\vec{h}_{t-1}AF_t + b_{\vec{h}}\right) \quad (6)$$

$$\overleftarrow{h}_t = S\left(W_{AF\overleftarrow{h}}AF_t + W_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h}_{t+1}AF_t + b_{\overleftarrow{h}}\right) \quad (7)$$

$$y_t = W_{\vec{h}y}\vec{h}_t + W_{\overleftarrow{h}y}\overleftarrow{h}_t + b_y \quad (8)$$

where S is the hidden layer function applied to each vector element, W stands for weight matrices, and b for bias vectors. Every NN unit in the BDLSTM network is an LSTM cell.

$$f_t = \sigma\left(W_{AFf}AF_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \quad (9)$$

$$i_t = \sigma(W_{AFi}AF_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (10)$$

$$o_t = \sigma(W_{AFo}AF_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (11)$$

$$c_t = f_t c_{t-1} + i_t \tan h(W_{AFc}AF_t + W_{hc}h_{t-1} + b_c) \quad (12)$$

$$h_t = o_t \tan h(c_t) \quad (13)$$

where f_t, i_t, o_t, c_t are the forget gate, input gate, output gate, and cell state at time step t, respectively, and σ is the logistic sigmoid function. The classification output of PD is obtained by feeding the BDLSTM network outputs to a fully connected layer.

4. RESULT AND DISCUSSION

In this section, the experimental setup of the PD-LSTM was implemented using MATLAB 2020b, and the ensuing experimental findings are represented. The PD-LSTM to evaluate the model on the collected voice signal, a number of measures were employed, including F1 score, recall, accuracy, specificity, and precision.

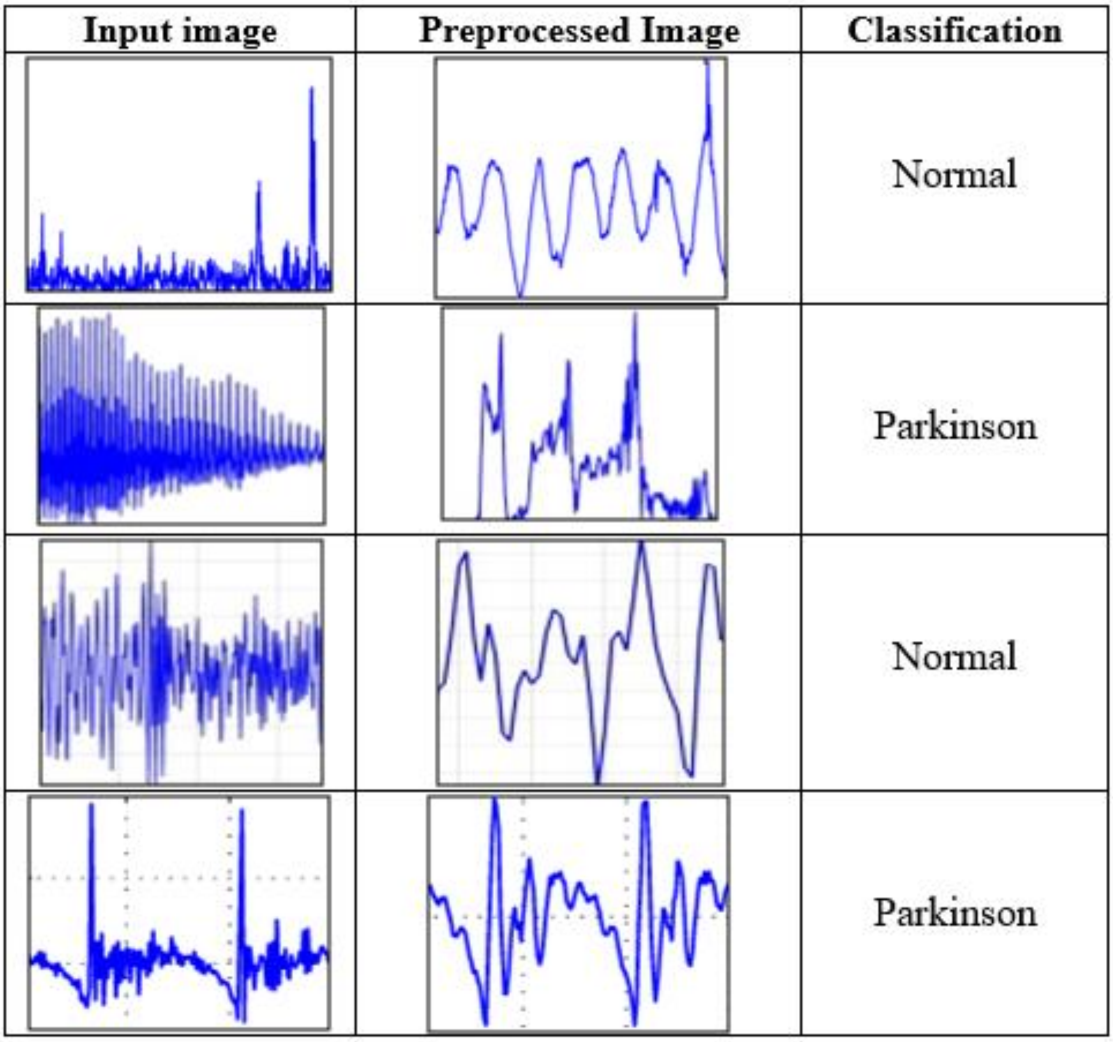

Figure 2. Experimental result of the PD-LSTM approach

The input images are obtained from the EWA-DB dataset, for voice signal as shown in column 1. In column 2, the Adaptive wavelet transform (AWT) is applied as a preprocessing step to reduce the noise. In column 4, BDLSTM is utilized for classification to determine whether the PD is Parkinson and normal. The experimental results of the PD-LSTM approach, are display in Figure 2.

4.1 Performance Analysis

The PD-LSTM approach was evaluated in this section utilizing several measurements like recall, specificity, F1 score, accuracy, and precision, in the gathered dataset.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{14}$$

$$Specificity = \frac{TN}{TN+FP} \tag{15}$$

$$Precision = \frac{TP}{TP+FP} \tag{16}$$

$$recall = \frac{TP}{TP+FN} \tag{17}$$

$$f_1 = 2(\frac{precision*recall}{precision+recall}) \tag{18}$$

where T_{pos} and T_{neg} indicates the True positive and negative of the provided images, F_{pos} and F_{neg} shows the sample images false positives and negatives.

Table 1. Performance analysis of the PD-LSTM model

Classes	Accuracy	Specificity	Precision	Recall	F1 score
Normal	99.11%	98.98%	98.57%	98.97%	97.58%
Parkinson	99.33%	98.11%	97.75%	96.99%	97.67%

Table 1 presents various classes, the proposed technique was evaluated for its recall, F1 score, specificity, accuracy, and precision. The accuracy of the PD-LSTM approach is 99.11% for normal and 99.33% for Parkinson disease.

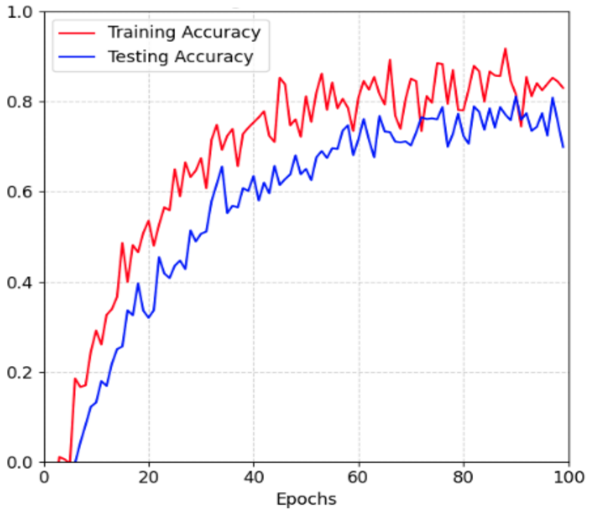

Figure 3. Accuracy of the proposed PD-LSTM model

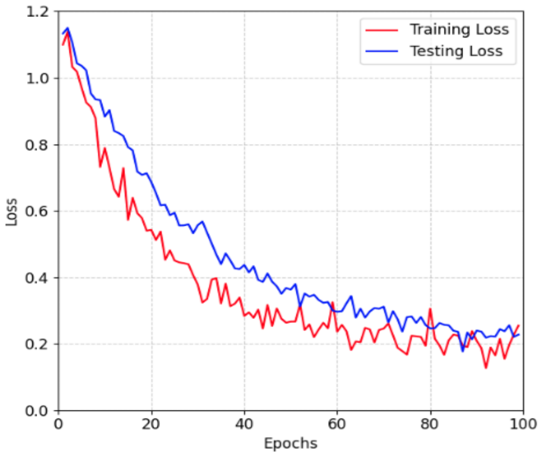

Figure 4. Loss of the proposed PD-LSTM model

Figure 3 displays the accuracy of the training and testing, with accuracy on the y-axis and Epochs on the x-axis. The proposed framework shows an accuracy level of 99.22% for times when considering the correctness of its evaluation and training curves. Figure 4 displays the loss graph displayed against epochs, demonstrating that the loss decreases as epochs increase. The proposed approach has a low loss of 0.78% while achieving great precision.

4.2 Comparative Analysis

The model shows strong performance in experimental conditions, real-world deployment in an IoT elder monitoring system requires testing under variable recording devices, network conditions, and edge compute constraints. The PD-LSTM methods accuracy and efficiency were demonstrated by comparing it to other existing methods. The BDLSTM approach was used to identify voice signal as normal and parkinson in order to measure the efficiency. Using metrics of recall, F1 score, accuracy, and specificity, the efficacy of the proposed approach is assessed. The accuracy rate demonstrates that the recommended approach of the existing methods. The PD-LSTM approach is contrasted with the existing techniques, including ZFNet-LHO-DRN [16], FB-DNN [17], and Ma-ST-DGN [20].

Table 2. Comparison of the existing model and PD-LSTM approach

Techniques	**Accuracy**	**Specificity**	**Precision**	**Recall**	**F1 score**
ZFNet-LHO-DRN [16]	89.81 %	85.28%	87.2%	89.13 %	88.23 %
FB-DNN [17]	96.15 %	95.35%	89.61 %	93.27 %	94.82 %
Ma-ST-DGN [20]	88.71 %	85.47%	87.33 %	86.41 %	82.75 %
Proposed	99.22 %	98.56%	98.16 %	97.98 %	97.62 %

Table 2 presents the various techniques of the existing model and compare the proposed model. The PD-LSTM technique improves the accuracy 89.81%, 96.15% and 88.71% better than the ZFNet-LHO-DRN [16], FB-DNN [17], and Ma-ST-DGN [20] respectively. The PD-LSTM approach outperforms the current methods with an accuracy of 99.22%. The PD-LSTM improves the accuracy range of 10.47%, 3.19% and 11.85% better than ZFNet-LHO-DRN [16], FB-DNN [17], and Ma-ST-DGN [20] respectively.

Table 3. Accuracy comparison of the existing models and PD-LSTM approach

Authors	**Method**	**Accuracy**
Saha et al., [15]	SVM	97.4%
Hasib et al., [18]	CNN	94.64%
Proposed	PD-LSTM	99.22%

Table 3 shows an Accuracy comparison of existing approach and the PD-LSTM approach. The PD-LSTM approach maintains high accuracy levels of 99.22%. The PD-LSTM approach enhances the total accuracy by 1.86%, and 4.83% better than SVM [15], and CNN [18] respectively. The comparison above indicates that the PD-LSTM approach is more accurate than the existing approach.

5. CONCLUSION

In this research, a novel PD-LSTM approach was proposed for the Parkinson disease classification using an BDLSTM. The input signals are pre-processed using the AWT to reduce the noise and enhanced signal. The MFCC is used to produce the discriminant features and SAE utilized to extract the features of a voice signal. The BDLSTM is used to improve the accuracy and classification such as normal and Parkinson. The performance of the PD-LSTM approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The PD-LSTM approach accomplishes a higher accuracy of 99.22% respectively. The PD-LSTM approach enhances the total accuracy by 1.86%, and 4.83% better than SVM, and CNN respectively. The PD-LSTM improves the accuracy range of 10.47%, 3.19% and 11.85% better than ZFNet-LHO-DRN, FB-DNN, and Ma-ST-DGN respectively. Moreover, the PD-LSTM approach can serve as the core classification module in an IoT-based elder monitoring system, enabling continuous remote detection of Parkinson's symptoms. Future work will validate the model in on-device/edge deployments and in diverse real-world IoT settings.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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