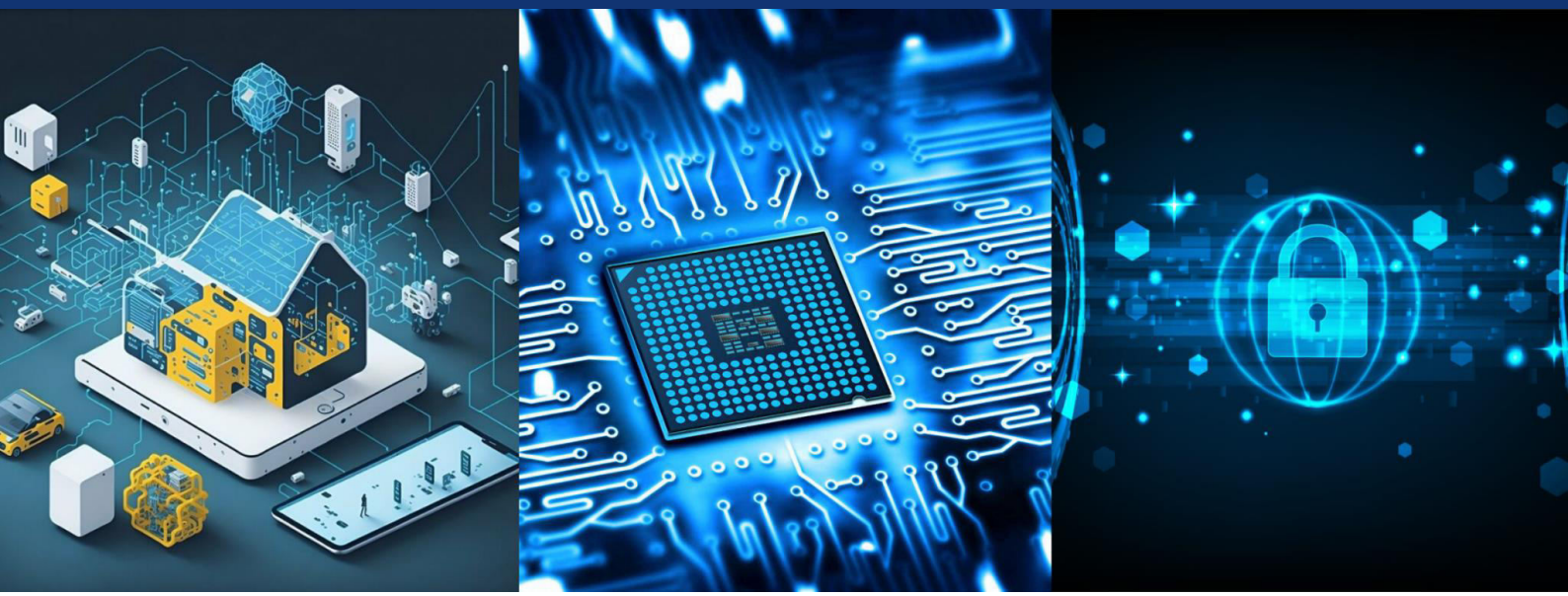
IJIRCCE

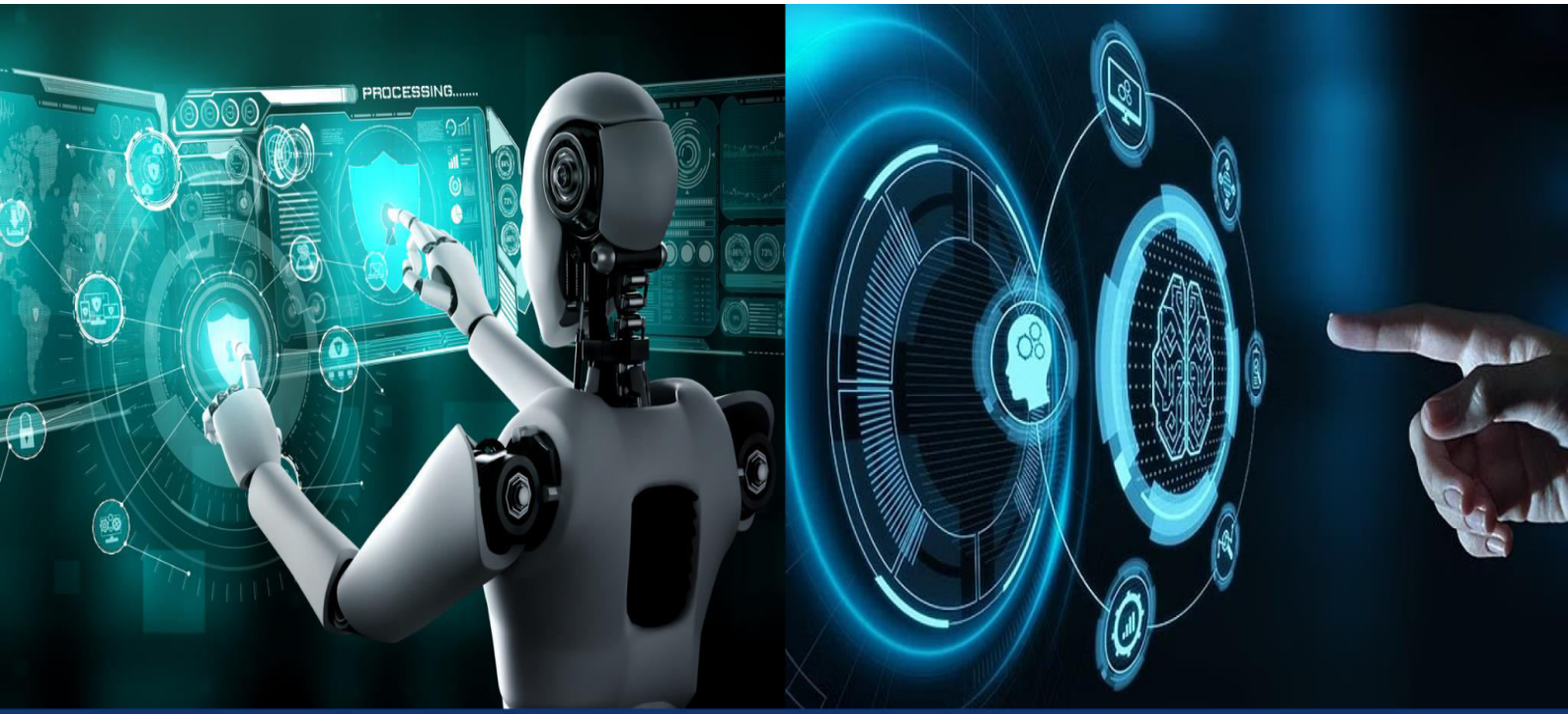
ISSN(O): 2320-9801

ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.771

Volume 13, Issue 4, April 2025

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Multi-Class Classification of Parkinson's Disease using Audio Signals and Deep Learning Models

Charan S, Barath Raj M, Samuael Elfege, Chandanapalli Kumar Babu

UG Students, Dept. of CSE, Puducherry Technological University, East Coast Road, Pillaichavady, Puducherry, India

Dr. Sheeba J I

Associate Professor, Dept. of CSE, Puducherry Technological University, East Coast Road, Pillaichavady, Puducherry, India

ABSTRACT: Parkinson's Disease (PD) is a neurodegenerative disorder that gradually impairs motor function and speech. Early and precise stage-wise diagnosis is essential for optimizing treatment strategies and improving patient outcomes. In this study, we have developed a deep learning-based model that classifies the severity of PD by analyzing voice recordings. Key speech features such as chroma, spectral contrast, tonnetz, jitter, shimmer, and harmonic-to-noise ratio were extracted using the Librosa library to capture both frequency-based and vocal stability characteristics. The model is built on a hybrid CNN and BiLSTM architecture, where the convolutional layers extract spatial patterns from audio spectrograms, and the BiLSTM layers track temporal changes in speech over time. Audio samples were preprocessed through normalization and frame slicing, and we used data augmentation techniques to handle class imbalance. To make the model user-friendly, we have built a Streamlit-based web app where users can upload their audio recordings and get immediate feedback, classifying their speech as Healthy, Mild, Moderate, or Severe. Using accuracy, precision, recall, F1-score and AUC as benchmarks, we validated the system's performance. The results highlight its potential as a practical, non-invasive solution for early Parkinson's detection and stage classification via speech analysis.

KEYWORDS: Parkinson's Disease; Speech Analysis; Deep Learning; CNN-BiLSTM; Multi-Class Classification; Streamlit UI

I. INTRODUCTION

Parkinson's Disease (PD) is a chronic and progressively debilitating neurological disorder that impacts a person's motor skills, speech, and overall quality of life. One of the earliest signs of PD often appears in speech, where subtle changes can signal the onset of the disease well before more visible motor symptoms emerge [4]. This makes vocal biomarkers an increasingly valuable tool for early diagnosis [6]. Traditional methods like neurological examinations and imaging techniques such as MRI or PET scans, while effective, tend to be expensive, time-consuming, and not ideal for continuous monitoring [1]. These limitations have driven growing interest in computational approaches, especially speech-based systems, for detecting PD and evaluating its progression [2].

Traditionally, speech-based diagnostic tools have used basic binary classification, separating healthy subjects from Parkinson's patients [6]. However, clinical practice requires a more detailed understanding — it's not just about identifying the presence of the disease, but also assessing its severity across different stages [8]. A single voice sample may reveal subtle differences indicative of mild, moderate, or severe PD, making multi-class classification a much more meaningful goal [9]. Despite this, many existing machine learning approaches still depend heavily on handcrafted feature sets or relatively shallow classifiers, which often fall short when it comes to capturing the complex, non-linear patterns in speech that evolve with disease progression [4].

To overcome these limitations, recent advances in deep learning offer significant potential [9]. Approaches using CNN architectures excel at identifying spatial patterns in spectrograms, while LSTM networks effectively model time-based relationships in speech data [9]. However, existing solutions often treat these features separately, missing

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

opportunities to detect subtle vocal variations linked to Parkinson's progression stages [4]. Our work bridges this critical limitation by introducing a novel architecture that merges CNN processing of spectrogram features with BiLSTM analysis of evolving speech characteristics, creating a unified framework for stage-specific detection.

For feature extraction, we use a diverse set of indicators including chroma, spectral contrast, tonnetz, jitter, shimmer, and Harmonic-to-Noise Ratio (HNR) to build a rich and comprehensive audio profile [4]. Preprocessing steps such as Z-score normalization and Pearson correlation-based filtering are also incorporated to minimize redundancy and focus on the most meaningful speech characteristics [1]. To mitigate class imbalance issues—especially when certain Parkinson's stages have limited samples—we enhanced our training data through augmentation techniques, improving the model's robustness and generalization capability [9].

While previous research has focused primarily on model architecture, our contribution extends to practical implementation [7]. The developed Streamlit web application enables real-time PD severity classification through intuitive audio uploads, bridging the gap between research and clinical utility [7]. This real-time capability can greatly enhance its use in both clinical environments and remote healthcare settings [8]. Rather than depending on costly diagnostic equipment or focusing solely on binary classification, this model aims to offer a scalable, affordable, and non-invasive solution for monitoring Parkinson's Disease over time [2].

This paper progresses through five key sections: First, we examine prior research and its limitations (Section 2). Next, we detail our methodology covering feature extraction, model architecture, and interface design (Section 3). Results and analysis follow in Section 4, with conclusions in Section 5.

II. LITERATURE REVIEW

In recent years, speech-based analysis has gained considerable attention as a non-invasive, cost-effective, and scalable method for diagnosing Parkinson's Disease (PD) [4]. Unlike traditional clinical assessments, which often involve expensive imaging and neurological examinations, speech analysis offers a promising alternative for both early detection and continuous monitoring [1]. Researchers have explored a wide range of machine learning and deep learning techniques to extract meaningful patterns from voice data and classify PD severity [8]. However, much of the early work in this area focused primarily on binary classification—simply distinguishing PD patients from healthy individuals—without addressing the more clinically relevant need to assess disease progression across multiple stages [6].

For instance, Jaisankar et al. (2025) developed a detection system using RFE for feature selection paired with logistic regression classification to identify early PD markers [1]. They introduced techniques like KMeansSMOTE for class balancing and used SHAP values to improve model interpretability [1]. While the approach achieved notable accuracy, it struggled to capture the complex, non-linear relationships and time-sequential patterns inherent in speech signals [1]. Similarly, Jyothish Lal et al. (2024) proposed a visibility graph method to transform multimodal biosignals, such as speech and gait data, into network graphs for enhanced severity classification [2]. Although the approach improved interpretability, it required high-quality multimodal data and came with significant computational costs, limiting its practical application [2].

Rather than voice analysis, Shin et al. (2024) quantified movement disorders through motion capture, demonstrating that SVM and Random Forest models could reliably classify PD severity based on kinematic data [3]. However, their method focused solely on motor symptoms and did not incorporate vocal biomarkers, making it less comprehensive for a full PD evaluation [3]. In another important contribution, Liu et al. (2023) developed a CNN-based system that analyzed phonation and articulation features such as MFCC and eGeMAPS across multiple languages [4]. While the model performed impressively, it was highly dependent on clean, high-quality recordings, which might not always be feasible in real-world scenarios [4].

Beyond speech-focused models, Sarapata et al. (2023) explored deep learning for video-based activity recognition by analyzing spatio-temporal pose estimations [5]. Their system achieved human-level accuracy in assessing motor symptoms but was highly computationally intensive and unsuitable for speech-only diagnosis [5]. Pah et al. (2023) evaluated the effectiveness of SVM classifiers using datasets like PC-GITA and Saarbrücken to distinguish PD voices

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

from those with other disorders [6]. The same architectures that excelled at binary detection failed to maintain comparable performance when extended to the more complex task of multi-stage severity classification [6].

Navamani et al. (2024) introduced an interpretable XGBoost-based model for PD prediction that used SHAP explanations to highlight important features [7]. Although the system handled class imbalance well, it lacked deep learning components needed to fully capture the intricate temporal dynamics of speech [7]. Hashim et al. (2024) attempted to improve diagnostic accuracy using a stacking ensemble of classifiers like SVM and Gradient Boosting, achieving strong results through bootstrapping [8]. Nevertheless, their system remained computationally expensive and did not leverage deep neural architectures [8].

Meanwhile, Pérez et al. (2024) experimented with Generative Adversarial Networks (GANs) to enhance voice-based time series classification through synthetic data generation [9]. Despite the innovative approach, models trained directly on raw waveforms underperformed compared to spectrogram-based systems, and training costs remained a significant concern [9].

Despite the progress made, significant challenges still exist [4]. Many models either focus solely on binary classification or require complex multimodal datasets, limiting their practicality for widespread use [2]. Moreover, deep learning models that can fully exploit the sequential and spatial features of speech signals for stage-wise severity prediction are still underexplored [4]. Combining audio-based CNN-BiLSTM architectures with structured preprocessing and intelligent feature optimization holds great promise for building real-time, accessible, and accurate PD diagnosis systems that can make a real impact both clinically and remotely [9].

III. METHODOLOGY

This study presents a structured framework for the early prediction and severity classification of Parkinson's Disease (PD) using speech signal analysis, as illustrated in Figure 1. The approach integrates advanced audio processing techniques with a deep learning-based model, and is organized into several key stages: data collection, feature extraction, preprocessing, model development using a hybrid CNN-BiLSTM architecture, and real-time user interface integration.

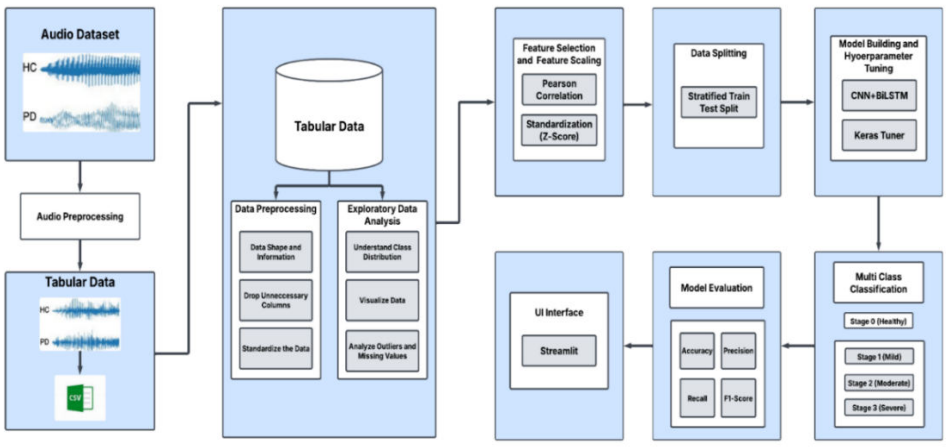


Fig.1. Proposed CNN-BiLSTM Hybrid Architecture

A. *Audio Preprocessing:*

The voice recordings used in this study were taken from a benchmark dataset, with each file containing a sustained vowel phonation of the /a/ sound. To ensure consistency and prepare the data for analysis, many preprocessing steps were applied. All the audio samples were normalized and resampled to a common sampling rate to maintain uniformity across the dataset. Silence trimming was performed to remove non-informative segments at the beginning and end of the recordings, focusing the model's attention on meaningful speech components. Additionally, these audio files were divided into fixed-length frames, with padding applied where necessary to accommodate recordings of varying durations.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

B. *Feature Extraction:*

We extracted key vocal biomarkers using Librosa's audio processing capabilities, capturing a comprehensive range of acoustic characteristics associated with PD. Chroma features quantified pitch characteristics in the speech signals, while spectral contrast and tonnetz features provided insights into the harmonic and timbral properties of the voice. Moreover, jitter and shimmer metrics were calculated to measure pitch variability and amplitude instability—both common symptoms of vocal tremor. The Harmonic-to-Noise Ratio (HNR) was also computed to assess the breathiness and hoarseness often found in PD-affected speech. As shown in Figure 2, mutual information-based feature selection was used to rank the top 30 extracted features by their relevance to Parkinson's classification, highlighting the most informative vocal attributes.

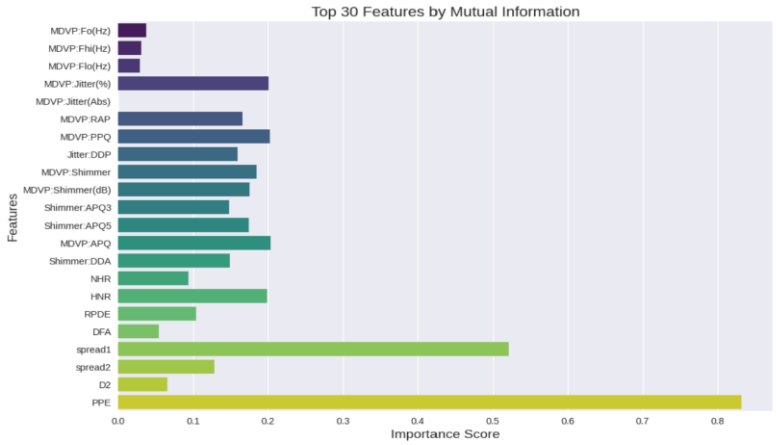


Fig.2. Feature Selection by Mutual Information

C. *Dataset Preprocessing and Feature Scaling:*

Before feeding the extracted features into the model,the data underwent further preprocessing to improve feature quality.We standardized the features via z-score normalization, centering them at zero with unit variance. Using Pearson correlation coefficients, we systematically identified and pruned interdependent features, optimizing the feature space to prevent overfitting while retaining diagnostic value.

D. *Dataset Splitting and Labeling:*

To preserve class distribution, we applied stratified sampling when partitioning the data into training and test sets, ensuring equal representation of Healthy, Mild, Moderate, and Severe cases. Labels for disease severity were encoded numerically to prepare them for the classification model.

E. *Model Architecture: CNN + BiLSTM Hybrid:*

Our hybrid architecture integrates CNNs to analyze spectral patterns in speech signals with BiLSTMs to model their sequential evolution—enabling comprehensive feature extraction across both frequency and time domains. CNN layers were used to extract spatial patterns from the spectrogram-like feature inputs, learning local acoustic structures that may indicate PD-related changes. The BiLSTM layers were designed to model temporal dependencies, processing sequences in both forward and backward directions to capture the progression of vocal signals over time. This architecture enabled precise identification of stage-specific vocal signatures, from subtle early-stage articulatory changes to pronounced late-stage speech degradation.

F. *Model Training and Optimization:*

We trained the CNN-BiLSTM model with Adam optimization and categorical cross-entropy as the objective function. Training was conducted over 80 epochs with a batch size of 32, and 20% of the training data was reserved for validation. Early stopping and learning rate scheduling were employed as callbacks to prevent overfitting and ensure smoother convergence during training.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

G. *Performance Evaluation:*

The model's performance was evaluated using several key metrics suitable for multi-class classification. Accuracy was calculated to measure overall prediction correctness, while precision, recall, F1-score and AUC were computed for each class to provide a more detailed assessment of model quality.

H. *Streamlit-Based Real-Time UI:*

To make the system accessible for practical use,we developed an interactive Streamlit-based interface for real-time PD severity visualization. In this platform, users can upload .wav audio recordings, trigger immediate predictions, and view the resulting classification into one of four categories: Healthy, Mild, Moderate, or Severe. This user-friendly interface paves the way for potential deployment in clinical settings or even at-home monitoring environments, offering a scalable, non-invasive solution for early Parkinson's screening.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. *Dataset:*

In order to evaluate the performance of the proposed multi-class Parkinson's Disease (PD) classification model, we conducted experiments using a publicly available speech dataset that includes sustained individuals and patients with PD .The dataset is accompanied by a demographics file that includes participant ID, age, gender, and condition label (Healthy Control or PwPD), and the speech recordings are used to distinguish between four disease stages: Healthy, Mild, Moderate, and Severe.

B. *Metrics:*

To assess the effectiveness and reliability of the proposed deep learning model, we use four key evaluation metrics commonly employed in multi-class classification:

Accuracy

Measures the proportion of all correct predictions (both positive and negative) out of all predictions made.

$$\text{Accuracy} = TP + TN / (TP + TN) + (FP + FN)$$

Precision

Measures the proportion of predicted positive labels that are actually correct.

$$\text{Precision} = TP / (TP + FP)$$

Recall

Assesses the ability of the model to capture all actual positive labels.

$$\text{Recall} = TP / (TP + FN)$$

F1 Score

The harmonic mean of Precision and Recall, balancing the trade-off between false positives and false negatives.

$$F1\ \text{Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

AUC

Measures the ability of the model to distinguish between positive and negative classes across all thresholds.

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

C. *Results and Visualization:*

To evaluate the classification performance of the proposed models for Parkinson's Disease (PD) severity prediction, many deep learning architectures were trained and tested. The models were assessed using key classification metrics: Accuracy, Precision, Recall, F1 Score, and AUC. These metrics collectively provide a balanced evaluation, especially crucial for multi-class classification tasks where both false positives and false negatives must be carefully monitored.

Table 1 represents a comparison of the performance metrics for all models. Among the evaluated models, the hybrid CNN-BiLSTM architecture achieved the best results, obtaining an accuracy of 75.75%, precision of 73.66%, recall of 75.75%,F1 Score of 66.87% and an AUC of 83.69%.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 1. Performance Metrics Comparison

Model	Accuracy	Precision	Recall	F1 Score	AUC
CNN-BiLSTM	0.7575	0.7366	0.7575	0.6687	0.8369
TCN-LSTM	0.7275	0.6329	0.7275	0.6433	0.8360
CNN-LSTM-Residual	0.6859	0.5751	0.6859	0.5991	0.8321
CNN	0.6744	0.6261	0.6744	0.6017	0.8323
Attention	0.6721	0.5114	0.6721	0.5807	0.8337
LSTM	0.6605	0.5036	0.6605	0.5711	0.8287
BiLSTM-Attention	0.6282	0.4757	0.6282	0.5402	0.8083
Transformer	0.5012	0.3838	0.5012	0.4342	0.7404

Figure 3 illustrates the training and validation accuracy and loss curves for the CNN-BiLSTM model across 80 epochs. The accuracy graph shows a consistent upward trend in both training and validation accuracy, stabilizing after around 40 epochs, indicating that the model generalizes well without significant overfitting. Similarly, the loss graph reveals a steady decrease in both training and validation loss, further confirming good learning behavior. The final validation accuracy closely follows the training accuracy, highlighting the robustness of the CNN-BiLSTM model's learning process.

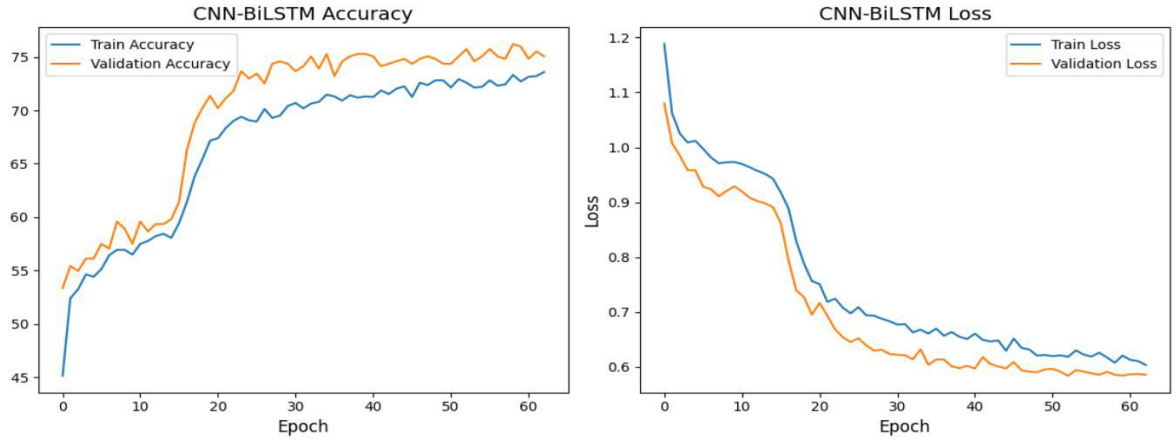


Fig.3. CNN-BiLSTM Model Accuracy and Loss Curves

Figure 4 presents a bar chart comparing different models based on Precision, Accuracy, Precision, F1 Score, Recall and AUC. From the visualization, The results demonstrate that the CNN-BiLSTM model consistently achieves superior scores across most metrics, further validating its performance. Particularly, CNN-BiLSTM and TCN-LSTM demonstrate higher AUC values, showing strong discriminative ability. On the other hand, models like the Transformer and BiLSTM-Attention performed comparatively lower across all metrics, emphasizing the advantages of the hybrid CNN-BiLSTM structure.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

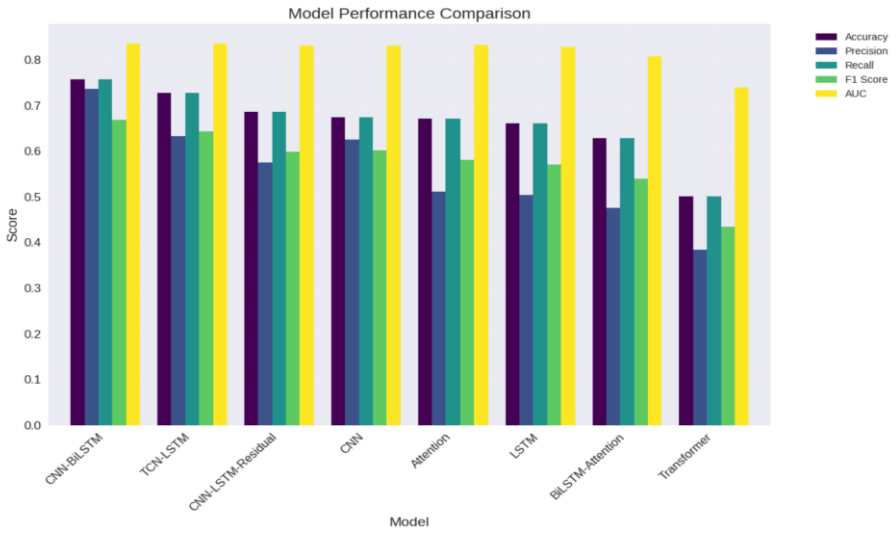


Fig.4. Model Performance Comparison

Figure 5 shows the confusion matrix for the CNN-BiLSTM model. The confusion matrix provides a detailed view of the model's prediction outcomes across different classes. It can be observed that the CNN-BiLSTM model classifies classes 1, 2, and 3 (representing different PD stages) with very high accuracy, as shown by the dense diagonal elements. However, for class 0, there is noticeable misclassification into neighboring classes, indicating some confusion in early-stage detection. Nevertheless, the overall distribution suggests that CNN-BiLSTM is highly effective, particularly in identifying moderate to severe PD stages.

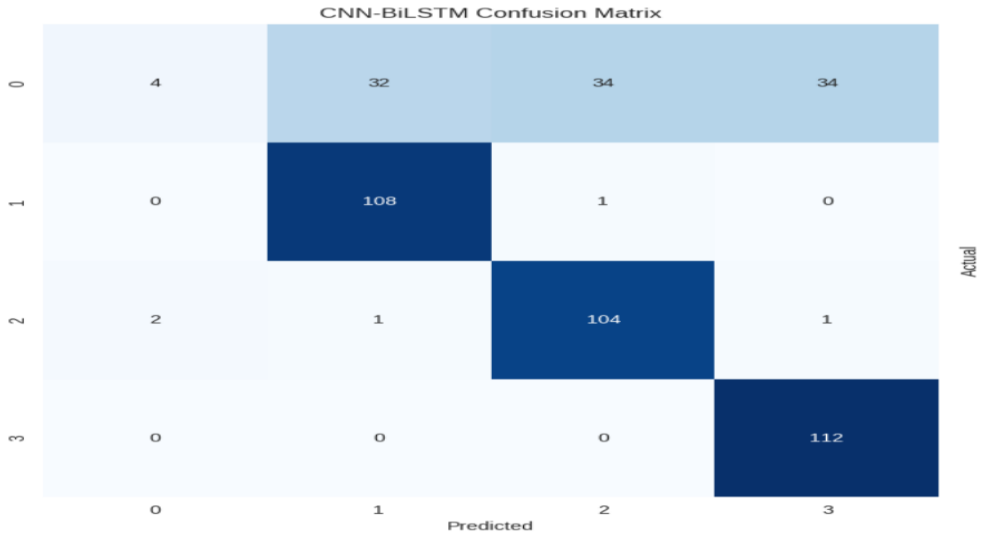


Fig.5. CNN-BiLSTM Confusion Matrix

Figure 6 displays the Micro-Average ROC Curve comparison among different models. ROC Curves provide insights into the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity). Among the models, CNN-BiLSTM achieved the highest AUC of 0.8369, indicating the best capability in distinguishing between different PD severity levels. CNN-LSTM-Residual and TCN-LSTM also exhibited strong performance, whereas the Transformer model demonstrated relatively poorer classification ability with the lowest AUC.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304289

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

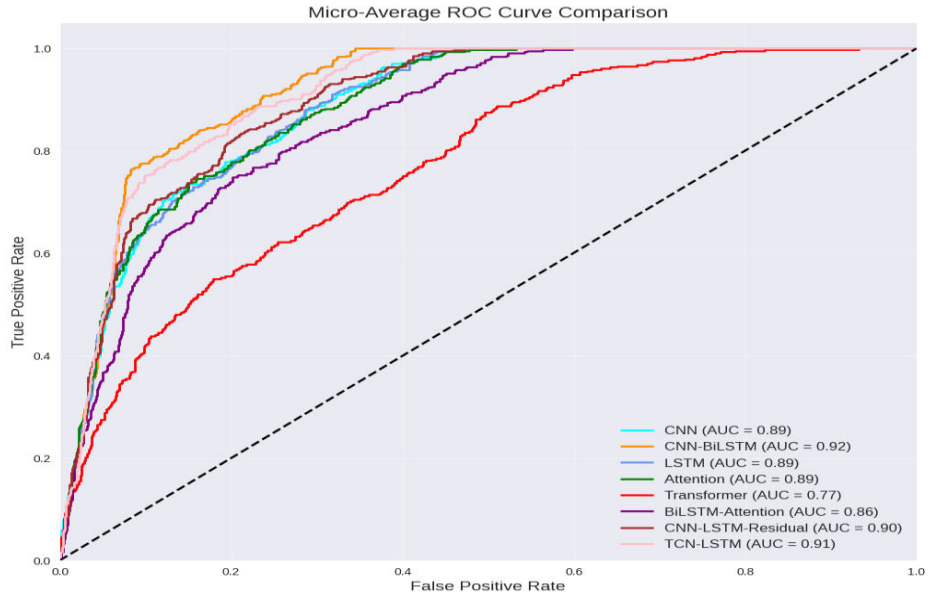


Fig.6. Micro-Average ROC Curve Comparison

The above graphs and table (Table 1, Figure 3, Figure 4, Figure 5 and Figure 6) collectively indicate that our proposed CNN-BiLSTM method achieves higher predictive accuracy, lower false detection rates, and better overall classification performance compared to existing models. These results emphasize the effectiveness of the hybrid CNN-BiLSTM architecture and its potential for real-world applications in early Parkinson's Disease diagnosis and remote health monitoring through non-invasive voice signal analysis.

V. CONCLUSION

This study presents a deep learning-based approach for the multi-class classification of Parkinson's Disease severity using speech signal analysis. By combining CNN and BiLSTM architectures, the model effectively captures both spatial and temporal characteristics of vocal patterns associated with PD. By combining the acoustic features such as jitter, shimmer, and HNR enhances the model's ability to differentiate between Healthy, Mild, Moderate, and Severe stages of the disease. Additionally, structured preprocessing techniques like Z-score normalization and Pearson correlation filtering contribute to feature relevance and dimensionality reduction. The deployment of the trained model through a Streamlit-based interface allows real-time, user-friendly interaction for PD stage prediction. Overall, the proposed framework demonstrates the potential for scalable, non-invasive, and accessible early-stage Parkinson's diagnosis using voice data.

REFERENCES

1. K. Velu and N. Jaisankar, "Design of an Early Prediction Model for Parkinson's Disease Using Machine Learning," in IEEE Access, vol. 13, pp. 17457-17472, 2025, doi: 10.1109/ACCESS.2025.3533703.
2. K. D. Raj, G. J. Lal, E. A. Gopalakrishnan, V. Sowmya and J. R. Orozco-Arroyave, "A Visibility Graph Approach for Multi-Stage Classification of Parkinson's Disease Using Multimodal Data," in IEEE Access, vol. 12, pp. 87077-87096, 2024, doi: 10.1109/ACCESS.2024.3416444.
3. J. Shin et al., "Classification of Hand-Movement Disabilities in Parkinson's Disease Using a Motion-Capture Device and Machine Learning," in IEEE Access, vol. 12, pp. 52466-52479, 2024, doi: 10.1109/ACCESS.2024.3386367.
4. Y. Liu, M. K. Reddy, N. Penttilä, T. Ihalainen, P. Alku and O. Räsänen, "Automatic Assessment of Parkinson's Disease Using Speech Representations of Phonation and Articulation," in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 31, pp. 242-255, 2023, doi: 10.1109/TASLP.2022.3212829.

5. G. Sarapata et al., "Video-Based Activity Recognition for Automated Motor Assessment of Parkinson's Disease," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 10, pp. 5032-5041, Oct. 2023, doi: 10.1109/JBHI.2023.3298530.
6. N. D. Pah, V. Indrawati and D. K. Kumar, "Voice-Based SVM Model Reliability for Identifying Parkinson's Disease," in IEEE Access, vol. 11, pp. 144296-144305, 2023, doi: 10.1109/ACCESS.2023.3344464.
7. K. Shyamala and T. M. Navamani, "Design of an Efficient Prediction Model for Early Parkinson's Disease Diagnosis," in IEEE Access, vol. 12, pp. 137295-137309, 2024, doi: 10.1109/ACCESS.2024.3421302.
8. R. M. Al-Tam, F. A. Hashim, S. Maqsood, L. Abualigah and R. M. Alwhaibi, "Enhancing Parkinson's Disease Diagnosis Through Stacking Ensemble-Based Machine Learning Approach," in IEEE Access, vol. 12, pp. 79549-79567, 2024, doi: 10.1109/ACCESS.2024.3408680.
9. Attaluri, V., & Mudunuri, L. N. R. (2025). Generative AI for Creative Learning Content Creation: Project-Based Learning and Art Generation. In Smart Education and Sustainable Learning Environments in Smart Cities (pp. 239-252). IGI Global Scientific Publishing.
10. M. Rey-Paredes, C. J. Pérez and A. Mateos-Caballero, "Time Series Classification of Raw Voice Waveforms for Parkinson's Disease Detection Using Generative Adversarial Network-Driven Data Augmentation," in IEEE Open Journal of the Computer Society, vol. 6, pp. 72-84, 2025, doi: 10.1109/OJCS.2024.3504864.
11. N. D. Pah, V. Indrawati, A. Prayitno and D. K. Kumar, "The Effectiveness of Acoustic Voice Quality Index to Identify People With Parkinson's Disease," in IEEE Access, vol. 12, pp. 172018-172026, 2024, doi: 10.1109/ACCESS.2024.3498836.

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details