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| RESEARCH ARTICLE

Multi-Omics System Based on Predictive Analysis with AI-Driven Models for Parkinson's Disease (PD) Neurosurgery

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| ABSTRACT
In addition to Alzheimer's disease, Bradykinesia, stiffness, tremor, and postural instability are symptoms of Parkinson's disease (PD), the second most prevalent neurological illness globally. The symptoms might overlap with those of other neurological diseases, making early identification difficult. This research investigates the possibilities of deep learning to detect PD through non-invasive voice analysis, which offers a practical and accessible diagnostic approach. Leveraging a biomedical voice dataset, propose to improve prediction accuracy and rectify the inherent class imbalance, a convolutional neural network (CNN) model can differentiate between healthy individuals and those with Parkinson's disease. SMOTE and feature selection strategies were employed. Experimental results demonstrate that the CNN model outperforms traditional classifiers, achieving a classification accuracy of 98.05%, as well as strong F1-score, precision, and recall. These results demonstrate how deep learning may help diagnose Parkinson's disease early and allow for quicker treatments. This study advances the development of voice-based, reasonably priced diagnostic tools for practical clinical applications.

| KEYWORDS

Neurodegeneration, Parkinson's Disease (PD), Early Diagnosis, Multi-Omics Integration, Precision Medicine, Machine Learning (ML), CNN, PD Data.

| ARTICLE INFORMATION

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1. Introduction

Inevitably, people age worldwide, and neurodegenerative diseases like PD and Alzheimer's are becoming more common. After Alzheimer's and PD neurodegenerative illness affects around 5% of those over 65. PD is caused by the substantia nigra's dopaminergic neurons degenerating.[1]. Among them, PD stands out as a complex, age-associated neurological disorder. It impacts more than 1% of those over 60. CMS, including bradykinesia, rigidity, and tremor, are the consequence of the slow death of the substance nigra monoamine neurons in PD [2]. However, these symptoms only become apparent after substantial neuronal loss, limiting the effectiveness of current pharmacological therapies [3]. Neurosurgical interventions, such as DBS and emerging laser nano-surgery techniques, offer symptomatic relief and show potential in neural circuit modulation and neuro restoration. Nonetheless, for these operations to be successful, careful patient selection and timing, ideally at earlier stages, are required when interventions may yield better outcomes [4].

This highlights the importance of identifying individuals at risk for PD before the start of any kind of motor problem. Prodrome symptoms that do not include movement, include rapid eye movement sleep behaviour problem, depression, hyposmia, and gastrointestinal complications, present a valuable window for early detection. However, current clinical diagnostic tools fall short in detecting these subtle, early manifestations [5]. To bridge this gap, A systems-level picture of the biological alterations that precede PD symptoms may be obtained by multi-omics approaches. These techniques incorporate information from transcriptomics, proteomics, metabolomics, genomes, and epigenomics [6]. Because multi-omics data is so large and complicated,

effective interpretation requires sophisticated computational techniques. AI models can be trained to integrate multi-omics and clinical data for early disease detection, risk assessment, and therapeutic planning [7][8].

Furthermore, AI has applications in neurosurgery, assisting in image-guided procedures, intraoperative decision-making, and postoperative outcome prediction, especially when integrated with omics-driven risk profiles [9]. AI-driven predictive analytics and advanced neurosurgical techniques represent a paradigm shift in how to treat PD [10]. This is where AI, particularly through ML and DL, becomes indispensable. These technologies enable the discovery of complex, nonlinear patterns in high-dimensional datasets, making it possible to predict PD onset, progression, and subtypes with high precision. This integrative approach offers a roadmap for transitioning from late-stage symptom management to early-stage disease interception. By enabling personalized, data-driven, and precisely targeted interventions, this model holds promise not only for improving patient outcomes but also for redefining how we understand and treat PD in the future.

1.1 Motivation and Contribution of Paper

This project aims to develop a speech signal early detection approach for PD that is non-invasive, accurate, and cost-effective. The signals should be simple to collect. Given the progressive nature of PD and the critical importance of early diagnosis for effective treatment, leveraging machine learning techniques, particularly a CNN-based model, offers a promising solution. The paper also discusses important issues including feature imbalance and redundancy, aiming in order of facilitate better clinical decision-making and improve the precision of diagnoses. The key contributions of the study are listed below:

- Utilized a voice signal-based biomedical dataset for non-invasive early detection of PD.
- Conducted comprehensive data pre-processing, including outlier detection, missing value handling, and standardization.
- Addressed class imbalance using the SMOTE technique to improve model generalization and fairness.
- To determine which voice characteristics are most important for PD prediction, RFE was used.
- Proposed a lightweight CNN architecture inspired by AlexNet, optimized for small biomedical datasets.
- Evaluated the model with multiple performance metrics (recall, accuracy, F1-score, precision, and ROC) to guarantee a thorough estimation.

1.2 Structure of paper

This document has the succeeding structure: Section II gives an outline of the literature on PD detection that is currently accessible. Section III outlines the proposed approach, which includes gathering and preparing data. Section IV discusses model implementation, experimental results, and key findings. Finally, Section V highlights the study's shortcomings and makes recommendations for future research possibilities.

2. Literature Review

This survey of the literature provides an extensive synthesis of recent studies focused on Identification of PD markers. The approaches are summarized in Table I, datasets, key findings, performance metrics, limitations, and proposed directions for future research.

Gil-Martín, Montero and San-Segundo (2019) Endeavour by examining a CNN for the recognition of PD based on the movements of drawings. They looked at how well different orientations could discriminate when drawing and found that X and Y were the most effective. Spiral Diagrams from PD This analysis made use of the freely accessible Digitized Graphics Tablet dataset. The optimal precision, F1-score, and AUC in this study were 96.5%, 97.7%, and 99.2%, respectively [11].

Polat (2019) found that LR modelling has identified the PD patients experiencing Fog. There are eight cases of PD in the dataset. An accuracy of 81.3% was attained in the classification of FoG patients with PD using acceleration data. According to the findings, the suggested approach might be utilised to identify and diagnose PD using only an acceleration sensor [12].

Wroge et al. (2018) investigate how well in order to diagnose the disease, Deep neural networks and other supervised classification techniques might be used. In a head-to-head comparison with industry experts, their ML models achieve an impressive 85% accuracy when using pathological post-mortem examination as ground truth. This significantly surpasses the average accuracy of movement disorder specialists, who achieve 83.9% with follow-up and non-experts (73.8%) in clinical diagnostics [13].

Viswanathan et al. (2018) Of the 40 participants in the trial, 18 had PD and 22 were controls. To distinguish between PD and healthy participants, the characteristics that were retrieved were used in an SVM classifier model. Phonation /m/ produced a 93% classification accuracy and a 0.85 MCC, while pronunciation /a/ produced a 70% classification accuracy and a 0.39 MCC. The results raise the possibility of using nasal consonant-corresponding features for PD diagnosis and tracking [14].

Wu et al. (2017) provide a gait sensing device that can identify PD patients from healthy controls by tracking how they walk about. One of their first products is a platform with force-responsive sensors that measure pressures. They proceed by gleaning gait characteristics from the gathered information. When compared to eight other models, the random forest model obtains a quantitative gait analysis accuracy of 92.49% for early PD identification, making it the clear winner, demonstrating the potential of this method experimental findings using nine distinct classifiers [15].

Agarwal, Chandrayan and Sahu (2016) suggested a productive method for reliably predicting Parkinson's illness utilizing voice samples and Extreme Learning Machines. For in on the training dataset, the suggested technique achieves a 90.76% accuracy rate and a 0.81 MCC when differentiating between healthy and PD patients. When evaluated using an independent dataset of PD patients, the suggested technique demonstrates an accuracy of 81.55%. The results show that the suggested approach is dependable for detecting PD [16].

Bhalchandra et al. (2015) Utilizing image processing, calculate radial and gradient characteristics derived from shape-based information extracted from SPECT images of 163 patients in the early stages of Parkinson's disease and 187 healthy controls drawn from the Parkinson's disease PPMI. The two are classified using support vector machines and discriminant analysis, utilizing these features and the SBR values, which are also given by the PPMI. A high classification accuracy of 99.42% is observed. According to the implication, these models may help physicians diagnose PD early [17].

Table I outlines ML for Parkinson's detection, guiding readers to see the variability in approaches, the strong accuracy levels and the different types of data used. Although progress is being made, studies are often restricted by small datasets, as bigger, multimodal inputs are needed and clinical use requires them to be validated.

Table 1: Summary of Recent Studies Parkinson disease prediction using machine learning

Author	Methodology	Datasets	Findings	Limitation / Recommendation
Gil-Martín, Montero & San-Segundo (2019)	Convolutional Neural Network (CNN) using FFT (0–25 Hz) of drawing movements	PD Spiral Drawings Using Digitized Graphics Tablet	F1-score: 97.7%, AUC: 99.2%; Accuracy: 96.5%, best performance with X and Y directions	Dataset limited to drawing tasks; recommend expanding to multimodal input for broader diagnosis
Polat (2019)	Logistic Regression, Linear/Quadratic/Cubic SVM, kNN	Acceleration signals from PD patients	Accuracy: 81.3% for FoG classification	Small sample size; more diverse data and larger cohort recommended
Wroge et al. (2018)	Supervised learning with Deep Neural Networks	Dataset with post-mortem validated PD diagnoses	Accuracy: 85%, outperforming non-expert and specialist clinical diagnosis	Suggests ML can assist diagnosis; real-world application needs larger validation
Viswanathan et al. (2018)	SVM classifier on phonation features (/m/, /a/)	40 subjects (18 PD, 22 control)	Nasal consonant /m/: 93% accuracy, MCC: 0.85; vowel /a/: 70% accuracy, MCC: 0.39	Limited subject pool; recommend further studies with more diverse phonetic samples
Wu et al. (2017)	Random Forest vs. 8 classifiers	386 subjects (218 healthy, 168 PD)	RF accuracy: 92.49%; demonstrates effective gait-based PD classification	Platform performance dependent on walking condition; field testing is needed
Agarwal et al. (2016)	ML Classification/ Supervised learning	Training and independent PD datasets	Training accuracy: 90.76%, Test accuracy: 81.55%, MCC: 0.81	Results show promise; larger datasets and real-time tests suggested
Bhalchandra et al. (2015)	SPECT image processing + SVM/Discriminant Analysis	PPMI: 163 PD, 187 healthy	Achieved 99.42% classification accuracy using shape features and SBR	Encourages adoption in clinical tools; needs integration with broader imaging diagnostics

3. Methodology

This study proposes a multi-omics predictive framework for PD neurosurgery outcomes. The study started by gathering and integrating a dataset of patients receiving neurosurgery for PD. Data pre-processing involves handling missing values, outlier detection based on feature skewness, and data type conversion. To address class imbalance, SMOTE was applied, resulting in a

balanced dataset. Standardization was then performed to normalize the data, followed by RFE to choose the characteristics that are most relevant to the target class. 20% of the testing set and a training set were created from the dataset. A two-convolutional-layer architecture is suggested for a condensed CNN. A sigmoid function was used by the output layer for binary classification. An extensive evaluation of the model's capacity to differentiate between PD and healthy instances was carried out using accuracy, precision, recall, F1-score, and ROC curves. Figure 1 depicts the suggested methodology's whole structure.

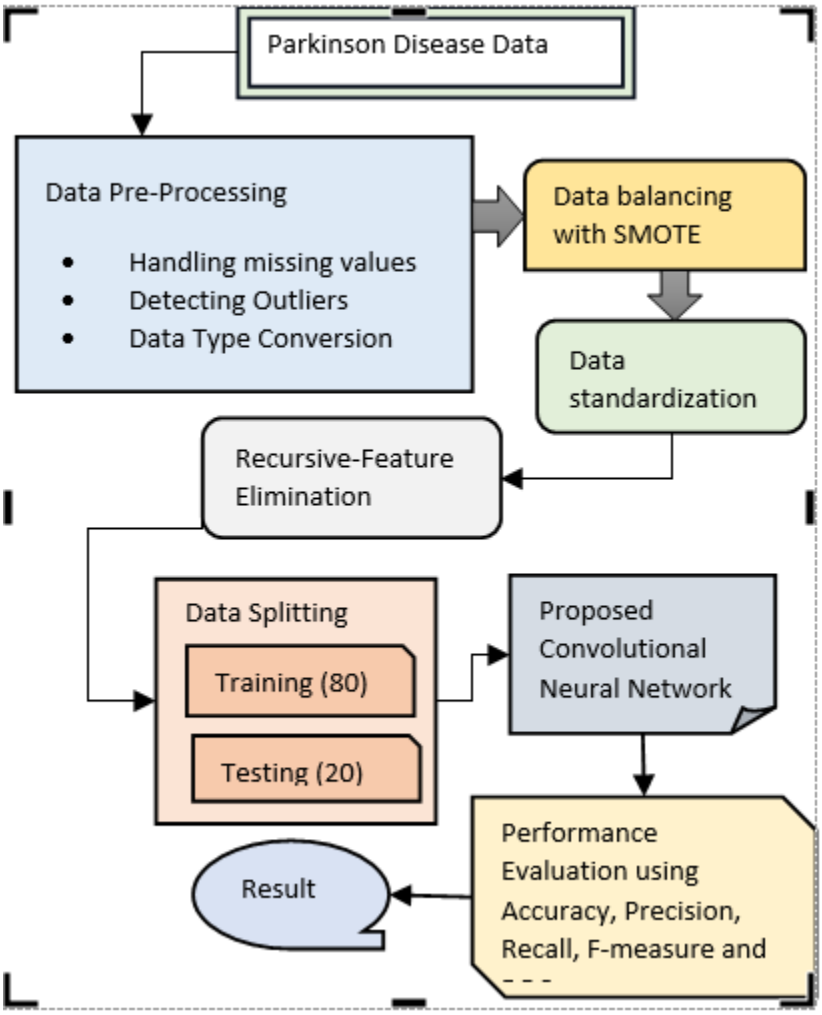

Fig 1: Flowchart for Parkinson Disease Detection

Below is an explanation of each phase and procedure in a flowchart and methodology:

3.1 Data Collection

The speech signal-based PD dataset used in this work for early PD identification was developed and contributed to the UCI ML Repository by Oxford University's Max Little. The 195 biological voices in the voice signal collection are separated into 48 phonetic categories for healthy individuals and 147 phonetic categories for PD patients. The following provides the data analysis and visualization:

Fig 2: Pie Plot for Data Distribution

Figure 2 displays a pie chart illustrating the training's class distribution dataset before the SMOTE algorithm. The chart reveals a significant class imbalance, with 75.2% of the data representing Parkinson's patients and only 24.8% representing healthy individuals. This imbalance indicates a potential bias in model training, as the categorizer might end up favouring the dominant group (Parkinson) over the minority class (Healthy), thereby highlighting the need for resampling techniques like SMOTE to ensure balanced learning and improve model performance.

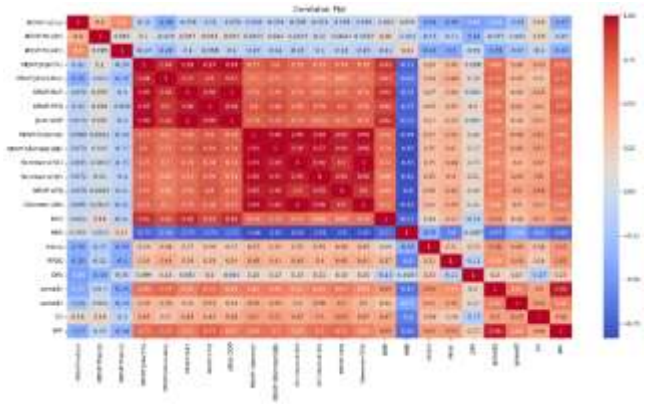

Fig 3: Correlation Heatmap of Data

Figure 3 illustrates the correlation heatmap of the dataset, highlighting the pairwise relationships between various features. Dark red cells deep blue cells have high negative associations, while deep blue cells show significant positive correlations. Interestingly, several MDVP-related features show high intercorrelation, suggesting potential multicollinearity, which is important to consider during feature selection or dimensionality reduction in model building.

3.2 Data Preparation

The act of transforming data processing is the process of transforming raw data into a usable and meaningful format. Processing. One of the most important procedures to guarantee the effectiveness of future actions is data analytics. The pre-processing involves outlier detection, data balancing, and standardization, which are discussed below:

- **Handling missing values:** Every feature in the dataset was carefully examined about blanks. Depending on the distribution and kind of the corresponding characteristics, suitable imputation methods, such as mean, median, or mode replacement, were used when missing values were found.
- **Detecting Outliers:** The PD dataset, comprising 23 voice features, was analysed for skewness to detect outliers. Features were grouped based on their distribution symmetry.
- **Data Type Conversion:** All numerical features in the dataset were confirmed to be continuous variables. The categorical feature, status, was converted to an appropriate categorical (object) data type to enable proper handling during analysis.

3.3 SMOTE for Data Balancing

SMOTE is a method that uses using pre-existing data on minority classes to generate new synthetic samples from that demographic using linear interpolation in order to enhance class balance and reduce over-fitting [18]. After applying SMOTE get a balanced dataset that illustrate in Figure 4.

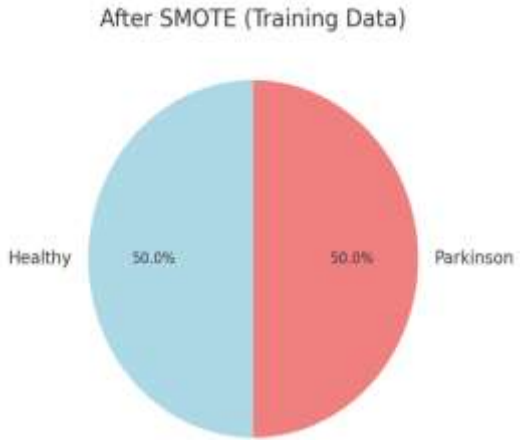

Fig 4. Pie Chart Balanced Data

Figure 4 depicting the class distribution of the training dataset after applying the SMOTE. The chart shows a perfectly balanced dataset, with 50.0% of the instances representing healthy individuals and 50.0% representing Parkinson's patients. This balanced distribution addresses the initial class imbalance and ensures that the ML model can learn equally from both classes, thereby enhancing its ability to generalize and improving its performance in detecting both healthy and Parkinson's cases accurately.

3.4 Standar Disation

In order to make certain that every piece of data had a uniform format, the standardisation approach was used. Equation (1), which divides the dataset's standard deviation by the overall average of every single feature's value, was used to standardise the dataset.

$$stand = \frac{x - mean}{Std\ Dev} \quad (1)$$

where: x = the original value of the feature, stand = the standardized value of x.

3.5 Recursive-Feature Elimination

Immediately following pre-processing, the connection between the features and the proportion of each feature that is positively and negatively correlated must be determined. The RFE algorithm, which seeks to determine the connection between each feature and the target feature, is used in this study. When it comes to choosing the most significant aspects that are associated with the successful prediction of the target feature and removing those that have a poor association with the status feature, the RFE algorithm is user-friendly, efficient, and effective. The association between the target feature and every dataset characteristic is shown in Figure 5.

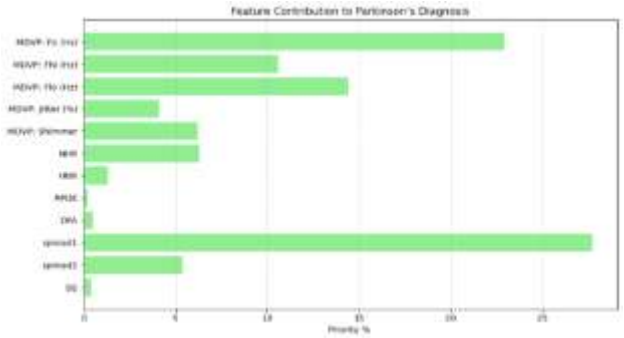

Fig 5. Bar Plot for Feature Contribution

Figure 5 illustrates the contribution of various features ranked by their priority percentage. The feature 'MDVP: Fo (Hz)' shows the highest contribution at approximately 22%, followed closely by 'spread1' at around 27%. Other significant contributors include 'MDVP: Fhi (Hz)' and 'MDVP: Flo (Hz)', both contributing over 10%. Features like 'MDVP: jitter (%)', 'MDVP: Shimmer', and 'NHR'

show moderate contributions between 2% and 6%, while 'HNR', 'RPDE', 'DFA', and 'D2' have minimal contributions, all falling below 2%. This visualization effectively highlights the most influential vocal features for Parkinson's diagnosis.

3.6 Train-Test Split

Data splitting refers to the process of dividing the dataset into subsets. The data are separated into sub-datasets containing training and testing in the ratio of 80:20.

3.7 Proposed Convolutional Neural Network (CNN)

CNN is divided into two sections: Two convolutional layers make up the first section, which takes into account 16 filters with 1 × 5 dimensions. Between the convolutional layers, we added a Max pooling layer in between. This section attempts to identify the key characteristics of the inputs [19]. Three completely integrated categorization layers are included in the second section. To prevent overfitting, dropout layers are included after convolutional and fully connected layers. Twenty percent of the weights were inactive. This design suggested simplifying the Alex Net CNN [20]. The CNN parameters were trained on a smaller dataset, necessitating this reduction [11]. The REL function every convolution layer employed was as its activation function. Along with the decoder and encoder, In the hidden layers of both, we used the REL function. You can see the REL function equation in Equation (2). The REL function is unique in that it always returns weights that are positive. Equation (3) shows that the output layer makes use of the sigmoid function. Following each convolution layer, a 2×2 pool size and 0.2 fallout probability two-dimensional max-pooling procedure was implemented [21].

$$f(x) = \max(0, x) \quad (2)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

In both cases, x represents the input (often a linear combination of weights and inputs, i.e., $x = \omega^T . input + b$) passed through activation function $f(x)$.

3.8 Performance Matrices of CNN Model

Accuracy, precision, recall, and F-measure are performance measures used to assess how well the various classification matrices work. The following is a definition of these measures:

1) Accuracy

One way to measure how many samples were correctly recognized is using the accuracy statistic. Here is how the accuracy for binary classification is calculated using Equation (4):

$$Accuracy = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \quad (4)$$

Where the –

- True Positives (T_p) reflect the appropriate allocation of illustrative instances,
- True Negatives (T_n) reflect the proper way to assign negative instances,
- False Positives (F_p) reflect the improper categorization of good instances into negative groups, and
- False Negatives (F_n) symbolize the improper categorization of negative instances into positive category.

2) Recall

The percentage of relevant topics that are located is assessed by the Recall measure. It assesses the classifier's capacity to provide all pertinent topics. The recall metrics is expressed below in Equation. (5):

$$Recall = \frac{T_p}{T_p+F_n} \quad \cdots$$

3) Precision

The accuracy measure determines what category of topics is applicable. The classifier's capacity to exclude unnecessary topics is evaluated. Equation (6) mathematically illustrates the accuracy:

$$Precision = \frac{T_p}{T_p+F_p} \quad (6)$$

4) F-Measure

The succeeding is the definition of the F-measure metric, which combines accuracy and recall in Equation. (7).

$$F1 - score = \frac{(1+\beta^2)Precision.Recall}{\beta^2 Precision+Recall} \quad (7)$$

where the degree of relevance of accuracy and recall is specified by β, a real positive weighting factor. To give accuracy and recall the same weight in this investigation, β is set to 1 [22].

5) ROC Curve

A graphical tool called a An example of a binary classification model would be determining whether a patient has PD; the ROC curve would be used to evaluate the model's performance in this case. The True Positive Rate (Sensitivity) may be observed at various threshold levels and compared to the False Positive Rate (1-Specificity) by using the ROC curve.

4. Results Analysis and Discussions

The simulation configuration and experimental findings of the CNN model applied to the PD dataset are presented in this part. A Windows 10 PC with a For this study, the researchers utilized a computer with a Risen 5 3600 (6-core CPU), 24 GB of RAM, an RTX 2060 Super graphics card, and the TensorFlow and Kera's Deep Learning Frameworks. The four primary metrics used to assess the model accuracy, precision, recall, and F1-score are summarized in Table II. With a high accuracy of 98.05%, the model performed a fantastic job at differentiating between individuals with PD and those without the disease. Not only that, it proved to be effective in identifying actual PD cases patients with a recall of 96.16% and a precision of 97.69%, indicating a low false positive rate. With an F1-score of 96.92%, which strikes a compromise between recall and accuracy, the CNN model's robustness and dependability in accurately categorizing PD were confirmed.

Table 2: Results of the proposed cnn for Parkinson's Disease Detection

Models	CNN
Accuracy	98.05
Precision	97.69
Recall	96.16
F1-score	96.92

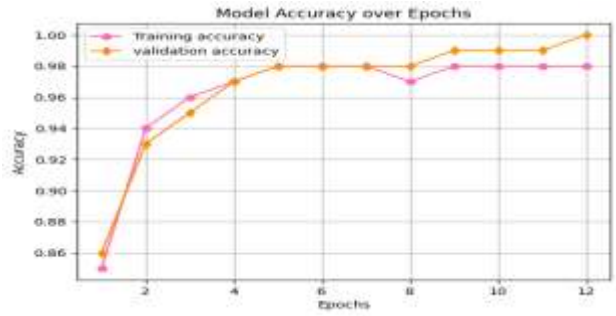

Fig 6: Plot Accuracy Curve for CNN

See Figure 6 for a 12-epoch rundown of the model's validation and training accuracy. Validation accuracy (orange line) and training accuracy (pink line) both show a significant increase in the first epochs, suggesting successful learning. While the instruction accuracy consistently rises and then stabilizes at a high level (around 0.98), the validation accuracy initially mirrors this trend but then surpasses the training accuracy from epoch 8 onwards, reaching a peak of 1.00 at epoch 12. This suggests that, in addition to learning well from the training data, the CNN model is also very good at generalizing to new data, potentially indicating a robust and well-performing model. Sources

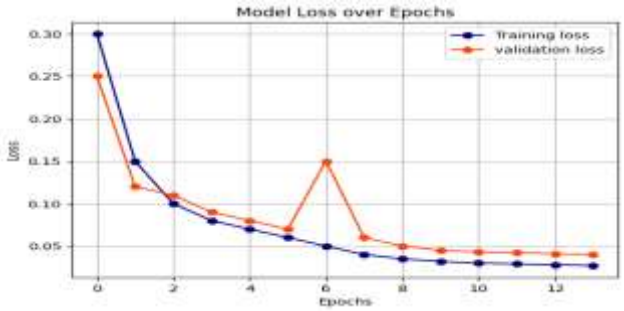

Fig 7: Plot Loss Curve for CNN

The model's validation and training losses during 12 epochs are shown in Figure 7. Both the validation loss (orange line) and training loss (dark blue line) often decline, suggesting that the model is picking up new information from the data. However, a notable spike in validation loss occurs around epoch 6, after which it resumes a decreasing trend but remains slightly higher than the training loss. This suggests that while the model is learning, it might be experiencing some overfitting, particularly around epoch 6, where its performance on unseen data temporarily worsens before improving again.

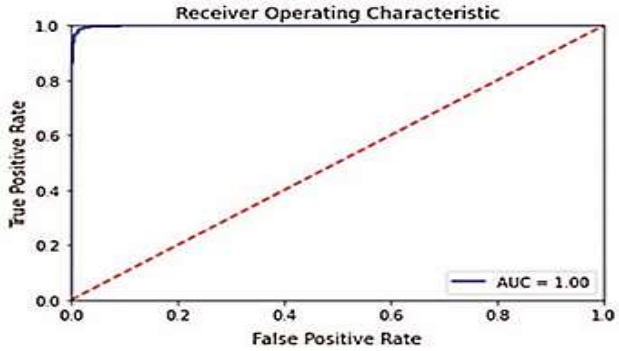

Fig 8. Plot ROC Curve for CNN

Figure 8 shows the x-axis Ratio of False Positives (1-Specificity) relative to the y-axis One measure of sensitivity is the true positive rate. The blue curve quickly rises to the upper-left corner before continuing along the top edge, signifying a flawless or near-perfect classification performance, which represents the model's performance. The fact that the AUC value is 1.00 lends credence to this. On the x-axis, we have the dashed red line representing the false positive rate (1-specificity), and on the y-axis, we have the true positive rate (sensitivity). This line extends diagonally from (0,0) to (1,1). The blue curve represents the model's performance; it first climbs steeply to the top left corner, and then it continues along the top until it reaches a certain point when it is completely accurate.

4.1 Comparative Analysis

In this part, we provide a thorough analysis of the alternatives of the proposed CNN model against several established algorithms, as shown in Table III. The Decision Tree (DT) model shows relatively modest performance, with an accuracy of 85.5% and lower precision (80%) and recall (72.7%), indicating limited reliability in identifying Parkinson's cases accurately. The MLP significantly outperforms DT, achieving an accuracy of 95.45% with balanced and high values across all metrics (precision, recall, and F-score at 95.5%), reflecting a well-rounded and effective model. The CNN model delivers the best performance overall, achieving 98.05% accuracy, with high precision (97.69%) and a strong F-score (96.92%). Despite a slightly lower recall (96.16%) compared to MLP, CNN demonstrates superior overall classification capability, making it the most effective model among the three for Parkinson's detection in this dataset.

Table 3: Various models' classification in parkinson Detection using PD Data

Model	Accuracy	Precision	Recall	F-Score
DT [23]	85.5	80	72.7	76.2
MLP[24]	95.45	95.5	95.5	95.5
CNN	98.05	97.69	96.16	96.92

The proposed CNN-based model offers significant advantages in the early detection of PD by utilizing non-invasive voice signal analysis, making it a practical and accessible diagnostic approach. Its ability to automatically learn discriminative vocal features without manual intervention enhances diagnostic accuracy and efficiency. The integration of SMOTE for data balancing and RFE for feature selection ensures robust model performance, even with limited and imbalanced datasets. Compared to traditional classifiers, the CNN model demonstrates superior accuracy, precision, and generalization capability, making it a promising tool for real-time, cost-effective, and scalable clinical support systems.

5. Conclusion and Future Work

The PD, a progressive neurodegenerative disease, affects dopamine-producing neurons severely, leading to a variety of non-motor problems as well as motor symptoms including tremors, stiffness, and delayed movement. For successful treatment, early discovery is essential. This research offers a CNN model using speech measures as a very successful method for PD identification. Using speech signal data, the suggested CNN model has shown remarkable accuracy (98.05%), precision (97.69%),

recall (96.16%), and F1-score (96.92%) in the early detection of PD. The prototype performs better than conventional classifiers like Multi-Layer and Decision Tree. Perceptron, confirming its robustness and generalization capability, as supported by ROC and learning curve analyses. Despite these promising results, the study faces challenges such as potential overfitting during training and the limitation of a relatively small and imbalanced dataset. Future research will focus on expanding the dataset with more diverse and larger samples, employing cross-domain validation, and exploring hybrid or transfer learning-based deep learning architectures to further improve model generalization, reliability, and applicability in real-world clinical settings.

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