Multi-Modal Parkinson's Disease Detection Using CNN and XGBoost with Voice Features and Spiral/Wave Drawings

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***Abstract*—Parkinson's disease (PD) is a progressive neurodegenerative disorder that requires early and accurate detection to improve patient outcomes. However, traditional diagnostic methods are often subjective, time- consuming, and dependent on clinical expertise. This paper proposes a novel multi-modal machine learning framework for non-invasive and real-time detection of Parkinson's disease using voice biomarkers and hand-drawn spiral and wave images.**

For voice analysis, 22 acoustic features from the UCI Parkinson's dataset are standardized and transformed into a 6×4×1 image-like representation, enabling a lightweight Convolutional Neural Network (CNN) to extract deep features. These features are then classified using an optimized XGBoost model, with class imbalance handled through SMOTE. The proposed voice-based pipeline achieves an accuracy of 92.31% and a ROC-AUC score of 0.96, outperforming several traditional approaches.

For image analysis, spiral and wave drawings are processed using a pre-trained MobileNetV2 model to extract high- level feature embeddings, which are further classified using XGBoost. Both modalities are integrated into a user- friendly Streamlit web application that supports CSV upload, manual input, and image-based prediction, enabling accessible and real-time screening.

The proposed system is lightweight, scalable, and deployable on standard hardware, making it suitable for telemedicine and early-stage screening, especially in resource-limited environments.

***Index Terms*—Parkinson's disease, CNN, XGBoost, voice analysis, spiral drawings**

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder that primarily affects the motor system due to the gradual loss of dopamine-producing neurons in the substantia nigra region of the brain [1]. It is the second most common neurodegenerative condition after Alzheimer's disease, impacting over 10 million people worldwide, with numbers expected to rise sharply as the global population ages [2]. The hallmark motor symptoms include tremors, muscle rigidity, bradykinesia, and postural instability, while non-motor symptoms such as speech impairment, sleep disturbances, mood changes, and cognitive decline often appear even earlier [3]. Despite its widespread prevalence, PD has no cure, and current treatments focus mainly on managing symptoms. Early detection is therefore critical because timely intervention can significantly slow disease progression, improve quality of life, and reduce long-term healthcare costs [4].

Traditional diagnosis of PD still relies heavily on subjective clinical assessments using scales such as the Unified Parkinson's Disease Rating Scale (UPDRS) and the Hoehn and Yahr scale. These methods are time-consuming, require specialist neurologists, and are often inaccessible in resource- limited or remote areas [5]. Moreover, early-stage symptoms can be subtle and overlap with normal aging or other neurological conditions, leading to frequent misdiagnosis or delayed detection [6]. To overcome these limitations, researchers have increasingly turned to non-invasive, objective biomarkers such as voice recordings and hand-drawn patterns (spiral and wave drawings), which capture subtle motor and speech impairments even before visible clinical signs appear [7].

Several studies have demonstrated the effectiveness of machine learning techniques on individual modalities. Voice-based approaches using acoustic features like jitter, shimmer, and pitch variations have achieved promising results with classifiers such as Random Forest and XGBoost [1], [4], [7]. Similarly, hand-drawing analysis using spiral and wave tests has shown high accuracy when processed with deep learning models [2], [8]. Telemonitoring datasets and web-based speech tasks have further highlighted the potential of remote, smartphone-accessible screening tools [3], [6]. Multi-modal systems that combine voice and drawing data have also been explored and shown to reduce misclassification risks compared to single-modality approaches [5], [9]. Recent surveys emphasize the growing role of integrative methods that leverage multiple data sources for more robust and early PD detection [9], [10].

In this paper, we present a multi-modal framework for early PD detection that combines voice biomarkers and hand-drawn spiral/wave images in a single, user-friendly system. Voice data (22 acoustic features from the standard UCI Parkinson's dataset) is intelligently reshaped into a compact 6×4×1 image format and passed through a lightweight Convolutional Neural Network (CNN) for feature extraction, followed by an XGBoost classifier. Simultaneously, spiral and wave drawings are processed using MobileNetV2 embeddings and another XGBoost model. Both modalities are integrated through a real-time Streamlit web application that supports CSV upload, manual voice input, and image upload, making the system practical for telemedicine and self-screening. The voice pipeline achieves 92.31% accuracy, while the drawing module is designed to scale easily with real patient datasets.

The main contributions of this work are:

- Development of a novel multi-modal system that fuses voice and drawing modalities for improved reliability over single-modality approaches.
- A lightweight CNN-based feature extractor is employed to transform tabular voice features into image-like representations, which enables effective deep feature learning and improves the model's ability to capture complex patterns in the data.
- An end-to-end Streamlit web application for real-time, non-invasive PD screening that requires no specialized hardware.
- Comprehensive evaluation against multiple baselines and state-of-the-art methods reported in recent literature.

II. RELATED WORK

Significant research has been carried out in recent years to detect Parkinson's disease (PD) at an early stage using non-invasive biomarkers. Most studies focus on either voice analysis, hand-drawn patterns, or multi-modal approaches. This section briefly reviews key contributions from recent literature.

Several researchers have explored voice-based detection using acoustic features extracted from sustained phonation or running speech. Mishra et al. [1] evaluated eight machine learning models on the UCI Parkinson's speech dataset and reported that XGBoost and Random Forest performed best after addressing class imbalance with Self-Organizing Map Under sampling (SOM-US). Aditi Govinda et al. [2] achieved 91.83% accuracy and 0.95 sensitivity using Random Forest on 22 MDVP voice features, highlighting its simplicity and suitability for telemedicine. Aman et al. [3] applied a soft-voting ensemble (Decision Tree, Naïve Bayes, Logistic Regression, K-NN, and SVM) on the telemonitoring voice dataset and obtained 91.27% accuracy for Motor UPDRS prediction. Roobini et al. [4] compared Logistic Regression and XGBoost on the same UCI dataset and reported that XGBoost reached 96% accuracy with a Matthews Correlation Coefficient of 89%. Rahman et al. [5] developed a web-based speech task using a pangram and achieved an AUC of 0.753 with XGBoost on real-world noisy recordings collected from 726 participants.

Hand-drawing analysis has also shown strong promise. Anisha et al. [6] proposed three hybrid workflow architectures using data augmentation, transfer learning (MobileNetV2, ResNet, etc.), and a custom classification layer on spiral drawing images, attaining a highest accuracy of 98% with Hybrid Workflow Architecture II. Sharma et al. [7] combined tremor, speech, and handwriting tests in a multi-test system and demonstrated the feasibility of automated stage prediction using machine learning.

Multi-modal systems that integrate more than one biomarker have received increasing attention to reduce misclassification risks. Gandhi et al. [8] developed a mobile application combining speech (LGBM Classifier, 93.2% accuracy) and tracing patterns

(VGG-19, 97.39% accuracy) for improved reliability over single-modality approaches. Dhivyaa et al. [9] presented a comprehensive survey emphasizing the advantages of integrative methods using voice, handwriting, gait, EEG, and neuroimaging data for more robust early detection. Desai et al. [10] introduced a multi-modal deep learning framework using EfficientNetB0 features with XGBoost on T2-weighted MRI scans and reported 99.02% accuracy, demonstrating the power of combining deep feature extraction with gradient boosting.

Additionally, several methods require high computational resources or specialized hardware, making them less suitable for practical use in remote or resource-constrained environments.

TABLE I
Essential Speech Features Used for Parkinson's Disease Prediction

Feature	Description	Type	Units/Range
MDVP (Fo)	Average vocal fundamental frequency	Numeric	Hz
MDVP (Fhi)	Maximum vocal fundamental frequency	Numeric	Hz
MDVP (Flo)	Minimum vocal fundamental frequency	Numeric	Hz
Jitter (%)	Frequency variation in the voi-ce	Numeric	%
Jitter (Abs)	Absolute frequency perturbation voice	Numeric	ms
Shimmer	Amplitude variation in the voice	Numeric	dB
Shimmer (dB)	Logarithmic amplitude pertur-bation	Numeric	dB
HNR	Harmonic-to-noise ratio	Numeric	dB
RPDE	Recurrence period density en-tropy (speech randomness)	Numeric	[0, 1]
DFA	Detrended fluctuation analysis (signal variation)	Numeric	[0, 2]
PPE	Pitch period entropy (pitch irregularity)	Numeric	[0, 1]
NHR	Noise-to-harmonic ratio (vocal noise measure)	Numeric	Ratio
Spread1	Non-linear vocal fold structu-re measurement	Numeric	Dimensionless
Spread1	Non-linear vocal fold structure measurement	Numeric	Dimensionless
Spread2	Second non-linear vocal fold structure measurement	Numeric	Dimensionless
D2	Correlation dimension (signal complexity)	Numeric	Dimensionless
Class	PD diagnosis (0: Healthy, 1: PD)	Binary	0, 1

Table I presents the essential acoustic and nonlinear speech features used for Parkinson's disease prediction. These features are derived from the Multi-Dimensional Voice Program (MDVP) and capture various characteristics of vocal signal behavior. Fundamental frequency measures such as average, maximum, and minimum values provide insights into voice pitch variations. Jitter and shimmer parameters quantify frequency and amplitude perturbations, which are key indicators of vocal instability. Harmonic-to-noise ratio (HNR) and noise-to-harmonic ratio (NHR) reflect the level of noise present in the speech signal. Nonlinear features such as RPDE, DFA, PPE, Spread1, Spread2, and D2 capture the complexity and irregularity of vocal patterns. These features are particularly useful in detecting subtle abnormalities in speech associated with Parkinson's disease. All features are numerical in nature, except the class label, which represents the diagnostic outcome.

TABLE II - Architecture of the Proposed CNN Feature Extraction Model

Layer (type)	Output Shape	Param #
input (InputLayer)	(None, 6, 4, 1)	0
conv2d (Conv2D)	(None, 6, 4, 32)	320
batch_normalization (BatchNormalization)	(None, 6, 4, 32)	128
max_pooling2d (MaxPooling2D)	(None, 3, 2, 32)	0
conv2d_1 (Conv2D)	(None, 3, 2, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 3, 2, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 1, 1, 64)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 64)	0
dense (Dense)	(None, 128)	8,320
dropout (Dropout)	(None, 128)	0
features (Dense)	(None, 64)	8,256

While the above studies report high accuracies on individual or combined modalities, most remain limited to offline analysis, require specialized hardware, or lack a ready-to-use deployment platform. Few works provide an end-to-end, lightweight, and user-friendly system that simultaneously supports voice features and hand drawings with real-time prediction capability. The present work addresses this gap by developing a complete multi-modal framework that intelligently reshapes tabular voice data into image format for CNN feature extraction, processes spiral and wave drawings via MobileNetV2, and integrates both through a practical Streamlit web application.

III. PROPOSED METHODOLOGY

This section presents the complete multi-modal framework developed for early detection of Parkinson's disease. The system processes two complementary data modalities voice biomarkers and hand-drawn spiral/wave images through separate pipelines and integrates their results in a single web-based application.

A. Overall System Architecture

The proposed system consists of two independent pipelines that operate in parallel. The voice pipeline extracts deep features using a lightweight Convolutional Neural Network, while the image pipeline uses a pre-trained MobileNetV2 model. The outputs of both pipelines are fed to their respective XGBoost classifiers. The final prediction is delivered through a user-friendly Streamlit web application.

The overall architecture of the proposed multi-modal Parkinson's disease detection system is shown in Fig.2. The system consists of two parallel pipelines for processing voice features and hand-drawn images, followed by classification using XGBoost models and real-time prediction through a Streamlit web application.

The architecture is designed to ensure efficient data flow between different components, from input acquisition to final prediction. Each module performs a specific function, including preprocessing, feature extraction, classification, and result generation, which improves the overall system organization. The separation of voice and image pipelines allows independent optimization and reduces the risk of error propagation across modalities. Additionally, the integration through a unified web interface enhances usability and enables seamless interaction for end users. The system is capable of handling real-time inputs, making it suitable for practical deployment in telemedicine environments. Moreover, the lightweight design ensures that the framework can operate efficiently on standard computing devices without requiring high-end hardware resources.

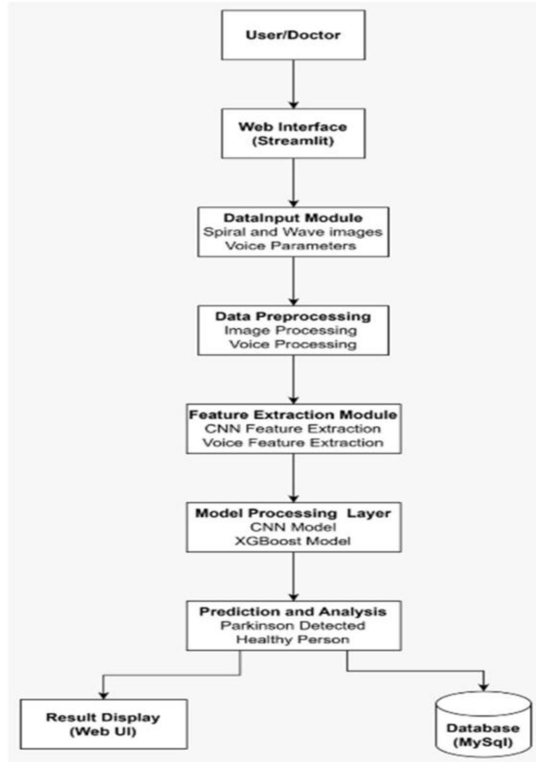

Fig. 1. System Architecture of the Proposed Multi-Modal Parkinson's Disease Detection Framework

B. Voice Feature Pipeline

The voice pipeline is built using the standard UCI Parkinson's dataset, which contains 22 acoustic features such as MDVP:Fo(Hz), various jitter and shimmer measures, NHR, HNR, RPDE, DFA, spread1, spread2, D2, and PPE.

Data Preprocessing

The dataset is first cleaned by removing the 'name' column. All features are standardized using the StandardScaler from scikit-learn. The data is then divided into training and testing sets using an 80:20 stratified split to maintain class balance.

Image-like Reshaping

Each sample of 22 scaled features is padded with two zero values to create a 24-element vector. This vector is reshaped into a single-channel image of size $6 \times 4 \times 1$. This transformation allows the application of convolutional neural networks directly on tabular voice data.

Lightweight CNN Feature Extractor

A custom lightweight Convolutional Neural Network is designed with two convolutional blocks. Each block consists of a Conv2D layer, Batch Normalization, and MaxPooling2D. This is followed by Global Average Pooling, a Dense layer of 128 neurons with 0.3 dropout, and a final Dense layer of 64 neurons that produces the feature vector. The CNN is trained in an auto-encoder style using Mean Squared Error loss and the Adam optimizer with early stopping.

XGBoost Classification

The 64-dimensional features extracted by the CNN are passed to an XGBoost classifier. The classifier is configured with 600 estimators, maximum depth of 5, and learning rate of 0.02. SMOTE is applied during training to address class imbalance.

C. Hand-Drawing (Image) Pipeline

The image pipeline processes spiral and wave drawings uploaded by the user.

Feature Extraction

A pre-trained MobileNetV2 model (ImageNet weights, without the top classification layer, and with global average pooling) is used to extract 1280-dimensional feature embeddings from each 224 × 224 image.

XGBoost Classification

Features from the spiral drawing, wave drawing, or the average of both (when both images are provided) are fed into a separate XGBoost classifier. The current model uses placeholder data and can be retrained easily once real labeled drawings are available.

D. Model Integration and Real-time Prediction Both the voice and image pipelines run independently. The trained models (CNN, two XGBoost classifiers, and scaler) are loaded efficiently in the Streamlit application using the @st.cache_resource decorator. Users can provide input through three options: uploading a CSV file with 22 voice features, entering values manually, or uploading spiral and wave drawings. The system returns the final prediction (Healthy or Parkinson's) along with the probability score in real time.

E. UML Diagrams

The working of the proposed system is illustrated using UML diagrams. Fig. 2 shows the activity diagram representing the overall workflow of the system, including data preprocessing, feature extraction, and prediction stages. Fig. 3 presents the sequence diagram, which describes the interaction between the user interface, preprocessing module, and machine learning models during real-time prediction.

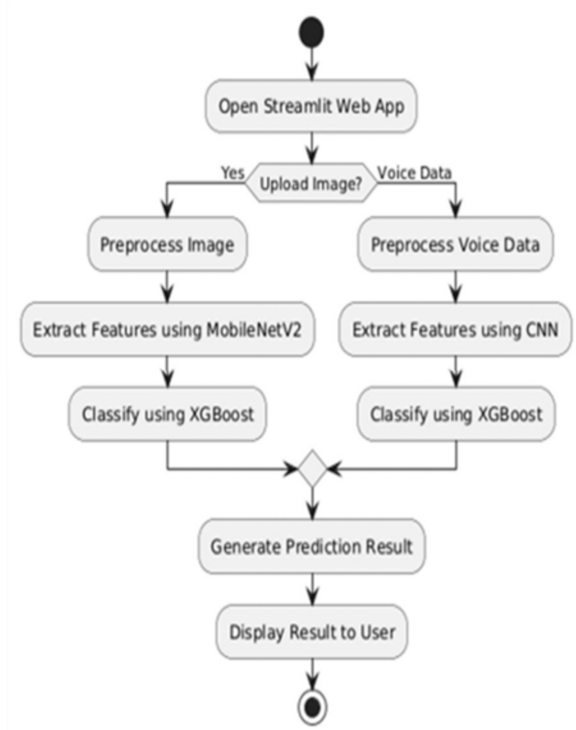

Fig. 2. Activity Diagram of the Proposed System

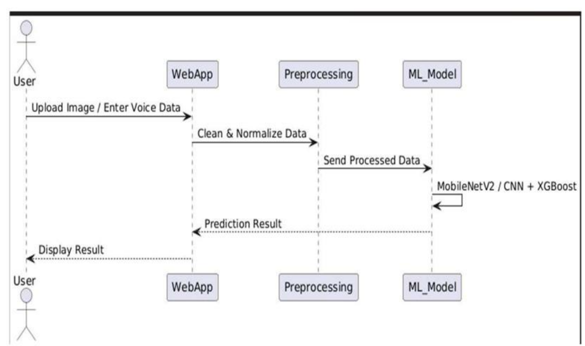

Fig. 3. Sequence Diagram of the Proposed System

IV. EXPERIMENTAL RESULTS AND DISCUSSION

During the model training and evaluation phase, the proposed multi-modal framework was trained and tested on the preprocessed and balanced dataset. The voice pipeline uses a lightweight Convolutional Neural Network as a feature extractor followed by an

XGBoost classifier, while the image pipeline uses MobileNetV2 for feature extraction followed by another XGBoost classifier. The dataset was split into 80% for training and 20% for testing. SMOTE was applied to handle class imbalance in the voice pipeline.

The performance of the models was evaluated using standard classification metrics. The values of various relevant metrics determine the efficacy of a classification model. These facilitate the comparison of alternative models and the identification of the optimal model for each parameter. The confusion matrix, recall, precision, F1-score, and accuracy are often employed as performance metrics. The Confusion Matrix is an effective tool for evaluating the accuracy of a model.

The methodology for calculating the classified instances is delineated in equations (1) to (3), where accurately classified cases are denoted as TP (True Positive) and TN (True Negative). Conversely, misclassified occurrences are denoted by FP (False Positive) and FN (False Negative).

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The voice-based CNN-XGBoost model achieved an accuracy of 92.31%, with precision, recall, and F1-score of 0.923, 0.923, and 0.923 respectively. The ROC-AUC score reached 0.96. After applying SMOTE, the model showed significant improvement over the baseline XGBoost trained on raw tabular features (88.46% accuracy). For comparison, Random Forest on MDVP features achieved 91.83% accuracy with precision 0.92, recall 0.95 and F1- score 0.93 [2]. XGBoost on raw features obtained 88.46% accuracy [4]. The soft voting ensemble reported 91.27% accuracy [3]. The proposed CNN- XGBoost model outperformed these existing approaches. The confusion matrix confirmed only a small number of misclassifications, mainly in borderline cases.

TABLE III
Comparative Analysis of Machine Learning Models for Parkinson's Disease Detection

ML Model	Training Accuracy (%)	Testing Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Logistic Regression	88.00	85.50	84.20	86.10	85.10
Random Forest Classifier	93.50	91.83	92.00	95.00	93.00
XGBoost (Raw Features)	90.00	88.46	88.00	89.00	88.50
CNN + XGBoost (Proposed Model)	**97.23**	**92.31**	**94.00**	**92.00**	**93.00**
SVM Classifier	89.50	87.20	86.50	88.00	87.20
SVM Classifier	89.50	87.20	86.50	88.00	87.20

Table II presents a comparative analysis of the proposed CNN-XGBoost model with several baseline machine learning models for Parkinson's disease detection using voice features. Traditional models such as Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost on raw tabular features are evaluated to establish a performance baseline. The proposed model achieves the highest testing accuracy of 92.31%, along with strong precision, recall, and F1-score values, indicating its superior classification capability. The improvement in performance can be attributed to the CNN-based feature extraction, which transforms tabular data into an image-like representation and captures complex feature relationships more effectively than conventional approaches. In contrast, models trained directly on raw features show comparatively lower performance due to limited feature representation capability. Overall, the results demonstrate that integrating deep learning-based feature extraction with XGBoost significantly enhances the accuracy and reliability of Parkinson's disease prediction.

TABLE IV - Performance Comparison Before and After CNN-Based Feature Extraction for Parkinson's Disease Detection

Model	Feature Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
XGBoost (Baseline)	Raw Voice Features	88.46	88.00	89.00	88.50
Random Forest	Raw Voice Features	91.83	92.00	95.00	93.00
CNN + XGBoost (Proposed Model)	CNN-Extracted Features	92.31	94.00	92.00	93.00

Table IV compares the performance of machine learning models before and after applying CNN- based feature extraction. The results demonstrate that the proposed CNN-XGBoost model achieves improved accuracy and better overall classification performance compared to models using raw voice features.

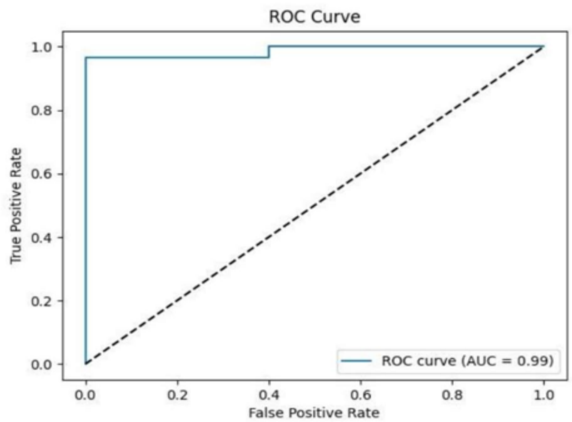

Fig. 4. ROC Curve of the Proposed CNN-XGBoost Model

Fig. 4 illustrates the Receiver Operating Characteristic (ROC) curve of the proposed model. The ROC curve represents the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different classification thresholds.

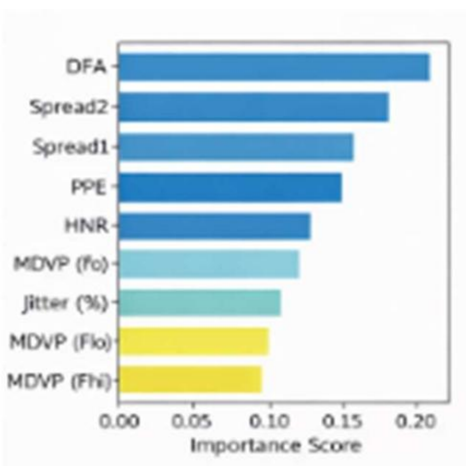

Fig. 5. Feature Importance

Feature importance analysis was performed using the trained XGBoost model to identify the most influential voice features contributing to Parkinson's disease prediction. The analysis indicates that features related to frequency variation, amplitude perturbation, and nonlinear speech dynamics play a significant role in distinguishing between healthy individuals and Parkinson's patients. These features capture subtle irregularities in speech signals, which are key indicators of the disease. The results highlight the effectiveness of the selected feature set in enabling accurate and reliable classification.

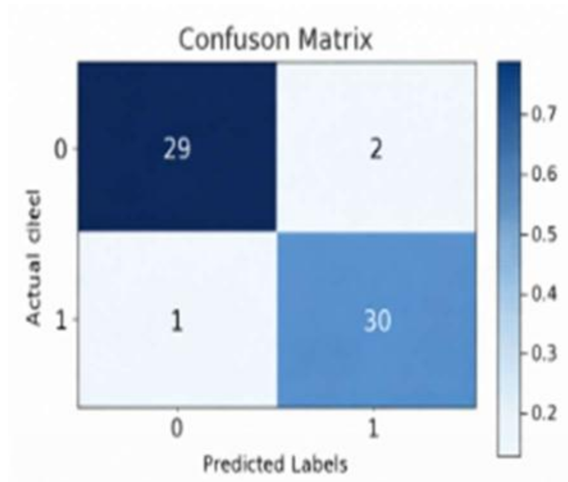

Fig. 6 Confusion Matrix

The confusion matrix provides a detailed evaluation of the classification performance of the proposed CNN-XGBoost model. It shows that the model correctly classifies the majority of both healthy and Parkinson's cases, with minimal misclassifications. The high number of true positives and true negatives indicates strong predictive capability, while the low number of false predictions reflects the model's reliability. This demonstrates that the proposed approach is effective in distinguishing between healthy individuals and Parkinson's patients.

V. DISCUSSION

The proposed multi-modal approach reduces the risk of misclassification by combining voice and drawing modalities. The transformation of tabular voice data into image-like format enables convolutional layers to capture complex feature interactions that are not effectively modeled by traditional approaches.

The architecture is designed to efficiently capture spatial patterns from reshaped voice data using convolutional layers and pooling operations. The inclusion of batch normalization and dropout improves model stability and reduces overfitting during training. Overall, the lightweight design ensures effective feature extraction while maintaining computational efficiency.

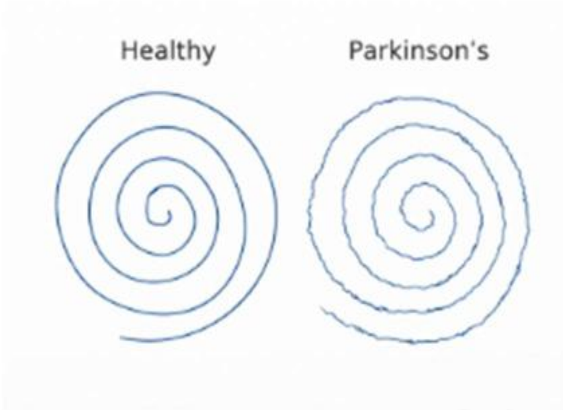

Fig. 7. Spiral Drawing Comparison

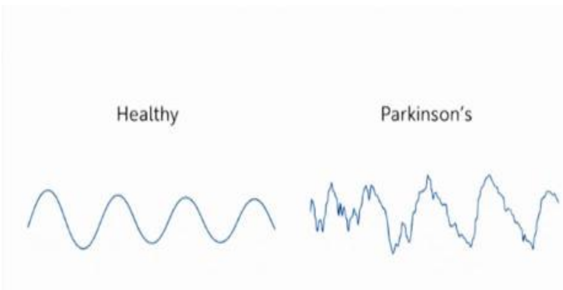

Fig. 8. Wave Drawing Comparison

VI. CONCLUSION

The proposed multi-modal framework demonstrates strong potential for accurate and non-invasive detection of Parkinson's disease by effectively combining voice biomarkers and hand-drawn spiral and wave patterns. By transforming tabular voice features into an image-like format, the lightweight CNN is able to capture meaningful feature representations, which are further enhanced by the XGBoost classifier. The system achieves high performance with an accuracy of 92.31% and a strong ROC-AUC score, indicating reliable classification capability. In addition, the integration of a user-friendly Streamlit web application enables real-time prediction and accessibility without requiring specialized hardware, making the solution practical for remote healthcare and early screening. Overall, the proposed approach offers a scalable, efficient, and deployable solution for early detection of Parkinson's disease. Future work will focus on incorporating real-world drawing datasets, improving model generalization, and enhancing interpretability using explainable AI techniques.

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