Multimodal Parkinson's Disease Detection Using Handwriting and Voice Analysis with Auto-Weight Fusion

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Abstract - *Parkinson's disease constitutes a progressive neurodegenerative disorder that persists long-term, which impairs both motor control and coordination and speech production abilities. The process of achieving effective treatment requires early diagnosis and precise diagnosis to enhance patient outcomes. The basic diagnostic methods depend on clinical assessments and neurological tests, which require significant time for their subjective nature to produce results. Automatic systems have been developed to perform more dependable detection work. This study introduces a multimodal machine learning framework that detects Parkinson's disease by analyzing handwriting images and voice-based acoustic features. The handwriting modality identifies motor disabilities, which researchers investigate through a MobileNetV2 transfer learning method that enables accurate feature extraction. The voice modality employs acoustic attributes that the XGBoost model classifies after applying preprocessing operations to scale features and eliminate unnecessary elements. The system uses an auto-weight optimization fusion method to merge both modalities, which calculates the optimal model contribution through classification success measurement. The handwriting model reached 87.6 percent accuracy, while the voice model achieved 95.8 percent accuracy according to experimental findings. The fusion model reached an overall accuracy of 89.3 percent, which showed better stability and equal performance across different tests. The proposed system delivers a non-invasive method that can detect Parkinson's disease early while providing decision support for clinical purposes through its economical and expandable design.*

Key Words: **Parkinson, Multimodal, Handwriting, Voice Signal, MobileNetV2, XGBoost, Fusion of Features.**

1. INTRODUCTION

Parkinson disease is a chronic and progressive neurodegenerative disorder, which involves the central nervous system and causes severe motor control, coordination, and speech production dysfunction. It is mainly brought about by the deterioration of neurons that produce dopamine in the brain, which interferes with the normal operation of motor pathways. A variety of motor symptoms are associated with the disease, such as tremor, rigidity, bradykinesia (slowness of movement), and postural instability. Along with these motor impairments are non-motor symptoms that are common in patients like voice difficulties, lack of speech clarity, and cognitive changes. The symptoms increase with the progression of the disease and thus early detection and intervention are important in preventing disease progression and improving the outcomes of the patient.

Conventional diagnostic methods of Parkinson disease are based on clinical observation, neurological examination and patient history. Although these techniques are commonplace, they tend to be subjective in nature and greatly rely on the knowledge and experience of medical practitioners. Addition�ally, the symptoms of the disease at the initial stages can be insidious and hard to detect, resulting in a delay in diagnosis and treatment. This constraint explains why automated, objective and data-based systems of diagnostic should be developed to help clinicians make more appropriate and timely decisions.

Over the past few years, machine learning and artificial intelligence have advanced, which has created new opportunities in the creation of such diagnostic tools. The methods facilitate the study of intricate biological signals and patterns that could be difficult to identify using conventional techniques. One of the data modalities, which have received a lot of focus, is handwriting and voice signals, as they are highly correlated with the symptoms of Parkinson disease. The analysis of handwriting can also help identify motor impairment, as it is common to find that the patient has tremors, deviant stroke patterns and slow writing. Likewise, voice analysis can detect vocal impairments like a decrease in pitch variation, hoarseness, and articulation, which are typical in patients with Parkinson's disease.

Though a number of studies have shown the usefulness of either handwriting or voice data alone, the use of a single modality might not be able to capture the numerous manifestations of the disease. The symptoms of Parkinson are diverse among different people and unimodal approach might not identify some pattern and hence the low reliability in diagnostic results. This has been the reason that has led to the exploration of multimodal frameworks that bring together several sources of information to give a more holistic evaluation.

Here, the current work suggests a multimodal machine learning model, which integrates handwriting and voice data to detect Parkinson disease. The transfer learning method with MobileNetV2 is used to analyze the handwriting modality as it facilitates the extraction of high-level spatial features of image data efficiently. In the voice modality, an XGBoost classifier will be used to model the acoustic features, which take advantage of its capability to use complex relationships in structured data. Moreover, an auto-weight optimization fusion method is proposed to merge forecasts of the two models. This is done in a dynamic way such that the optimal contribution of each modality is established resulting in a balanced and robust classification result.

The main goal of this paper is to improve the accuracy, reliability and strength of the detection of Parkinson disease based on complementary information of various modalities. The proposed system will be used to offer an affordable, scalable, and non-invasive motor and vocal biomarker system capable of aiding in early screening and helping medical specialists to make clinical decisions.

2. LITERATURE SURVEY

With the high rate of development of the computational intelligence and medical technologies, the process of diagnosis of neurodegenerative diseases, especially Parkinson Disease (PD) has undergone a profound change. PD is a progressive neurodegenerative disease that results in motor and non-motor symptoms (e.g. cognitive impairment and speech difficulties) due to degeneration of dopaminergic neurons causing motor symptoms in the form of tremors, rigidity, and gait impairment. Early diagnosis is a complicated issue because of its non-homogenous character and slow development. This has prompted many studies aimed at creating automated, data�driven solutions to proper and prompt detection.

Early studies on PD detection were based on the use of conventional machine learning algorithms and hand-crafted features. Physiological cues, including gait, speech patterns, and handwriting, were the main cues analyzed by these methods.

Gait analysis is a diagnostic measure that has been extensively explored in sensor-based time-series measurements. Walking patterns were captured by applying models like Artificial Neural Networks (ANN), linear regression and gradient boosting techniques. Although ANN and the boosting-based models were found to be more accurate in prediction, simpler models were found to be more explainable and there was a trade-off between accuracy and explainability.

Likewise, speech analysis has also been widely employed in detecting PD. Acoustic features that were extracted in the voice recordings included pitch variation, jitter, shimmer and harmonic-to-noise ratio. Algorithms such as Support Vector Machines (SVM) and Random Forests were used to classify these features. These methods were rather moderate in terms of accuracy but the performance was highly dependent on feature selection, which constrained their robustness and generalizability. Another method that is frequently employed is handwriting analysis since PD patients tend to have micrographia, or a small writing size and non-uniform patterns. The use of machine learning to recognize early symptoms in spiral and wave drawings has demonstrated good results. Nonetheless, these methods tend to have problems with variable data and they are not scalable to real-world situations.

With the advent of deep learning, PD detection has greatly enhanced with the automatic extraction of features in raw data. In contrast to the classical approaches, deep learning models do not require manual feature engineering and have the capability to identify intricate patterns in data.

Convolutional Neural Networks (CNNs) have been popularly used in medical image, spectrogram, and handwriting analysis. These models are able to capture spatial and temporal dependencies and hence can be used to detect subtle abnormalities related to PD. In speech-based detection, voice signals (spectrogram representations) have been presented to CNN models. Such representations retain both frequency and time information, enabling models to detect subtle deficiencies in the voice. The current literature with pre-trained CNN structures, including DenseNet, MobileNet, and ShuffleNet has shown high classification rates with a majority being above 95 percent, which illustrates the power of deep learning in speech recognition.

Handwriting-based diagnosis has also been effectively implemented with deep learning. The high accuracy of transfer learning methods based on pre-trained models like ResNet and GoogLeNet take advantage of pre-learned features. The performance has been further enhanced by the use of hybrid models that combine several architectures by exploiting complementary features and the effectiveness of deep fusion techniques is proved.

Single-modality methods have demonstrated encouraging outcomes, but they tend to be inadequate to describe the whole complexity of the Parkinson Disease. The recent studies have thus been on multimodal techniques that combine various data sets like clinical data, imaging, speech and genetic data.

To model relationships between patients and predict dis ease progression, graph-based models have been presented. The models combine several data modalities such as MRI scans and clinical tests to make individual predictions. These methods have demonstrated better capability to capture the heterogeneity and progression patterns of diseases.

The combination of deep learning and classical machine learning models has been considered as well. Deep learning models are employed in feature extraction and classical algorithms in classification in these systems. The purpose of this combination is to obtain high accuracy and better interpretability which is one of the greatest limitations of deep learning.

One of the major flaws of single models is the fact that they cannot describe all the pertinent aspects of PD. In order to deal with this, feature fusion methods and ensemble learning methods have been widely used. In feature fusion, the output of several models is used to come up with a more detailed model of the data. This methodology allows to combine the complementary information of various architectures, which results in better generalization and strength.

Ensemble learning algorithms like bagging, boosting and stacking also improve the performance of the model by combining the results of multiple models. XGBoost and gradient boosting algorithms have demonstrated good performance to model detailed patterns of gait and speech data. These methods enhance predictive accuracy and minimize model variance.

Although the PD detection has achieved a lot, there are still several challenges. The first and one of the biggest challenges is the heterogeneity of data because symptoms differ greatly among patients. This inconsistency causes models to be unable to generalize across datasets. The other problem that is critical is the lack of big and quality data. Small datasets are used in many studies, which can lead to overfitting and decrease model reliability. Data augmentation and data transfer learning are effective methods to alleviate this problem but they are not the solution to it.

Also, deep learning models tend not to be interpretable. Although they are very precise, their decision making is hard to follow and hence they cannot be used in clinical settings where transparency is a vital requirement.

Moreover, much of the current solutions concentrate on only one type of data, which is not the comprehensive measure of PD. Whereas multimodal approaches resolve this drawback, they need more complicated architectures and increased computation resources. Trends in recent research point towards the change toward personalized and non-invasive methods of diagnosis. The modeling of patient-specific disease progression is becoming more commonly done using graph-based models and deep learning architectures. Voice analysis and wearable sensors are increasingly used as they are non-invasive and cost-effective. Wearables can be constantly used in monitoring motor symptoms, which is useful in early detection and disease management. PD detection systems are also being equipped with explain able Artificial Intelligence (XAI) methods to enhance interpretability. Attention mechanisms and visualization techniques are some of the methods used to identify significant factors that contribute to model predictions.

Also, the transfer learning is still having a vital role in enhancing the performance of models particularly with limited data. Pre-trained models can be used to extract features efficiently and enhance accuracy without the need to use big datasets.

In short, the literature presents a shift in the methods of traditional machine learning towards the sophisticated deep learning and multimodal systems of detecting Parkinson's Disease. Although the initial approaches were based on manual feature extraction, recent approaches take advantage of automated feature learning and data integration. Multimodal, ensemble learning, and feature fusion have become important performance improvement strategies. Nevertheless, data variability, small datasets, and non-interpretability are issues that should be overcome to make it possible to apply the approach in practice.

3. PROPOSED METHODOLOGY

The given system is created as a multimodal model of the Parkinson Disease (PD) detection that integrates the analysis of images of handwriting and the classification of the voice-based acoustic features. The system is a combination of concepts of both deep learning and machine learning to capture motor and vocal impairments that are associated with PD.

3.1 System Overview

The overall architecture will have a parallel processing pipeline where handwriting and voice data is processed in dependently and the results combined using a fusion strategy.

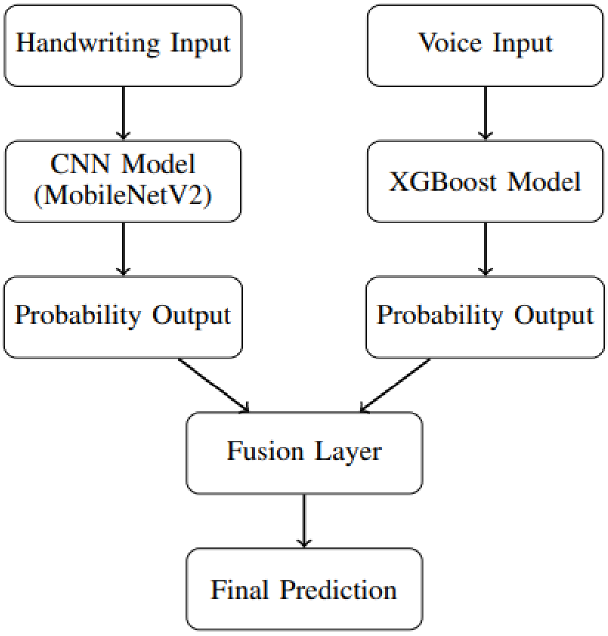

Fig. 1. Proposed Multimodal System Architecture

3.2 Handwriting-Based Detection

The handwriting modality captures motor impairments such as tremors, irregular strokes, and reduced writing precision.

1) Data Preprocessing: Input images are resized to 224×224 pixels and normalized. Grayscale images are con�verted to three-channel format to match the requirements of pre-trained convolutional neural networks.

2) Model Architecture: A base model is MobileNetV2 and a transfer learning technique is employed. Convoluted layers are then frozen to store learned characteristics and binary classification custom classifier is included. This model is trained with the Binary Cross Entropy loss and optimized with Adam optimizer.

3.3 Voice-Based Detection

The voice modality records the acoustic deviations like change in the pitch and amplitude.

1) Data Processing: The dataset contains voice features that researchers extracted from speech recordings. The dataset removes unnecessary attributes which include subject ID and duplicate variables. A binary label is created based a threshold which researchers applied to the UPDRS score.

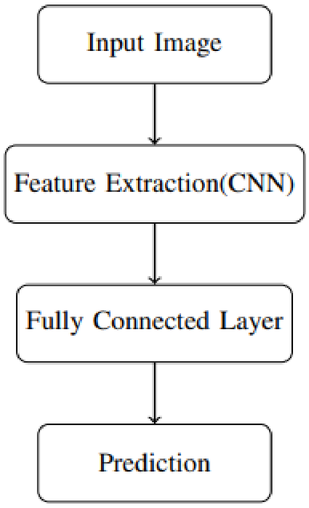

Fig. 2. Handwriting CNN Pipeline

2) Feature Scaling: Standardization is done to ensure every feature of the data has zero mean and unit variance, consequently increasing model stability.

3) Model Architecture: An XGBoost classifier is used due to its ability to model complex relationships in structured data.

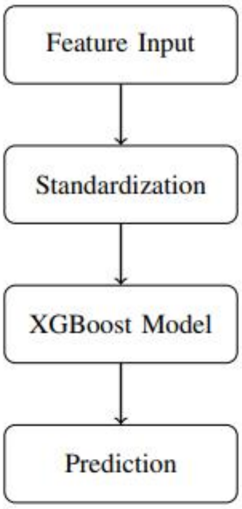

Fig. 3. Voice Classification Pipeline

3.4Fusion Strategy

The outputs of both models are combined using a probability-based fusion approach.

$$P_{fusion} = w \cdot P_{handwriting} + (1 - w) \cdot P_{voice}$$

(1) where w represents the weight assigned to the handwriting model. 1) Weight Optimization: In order to set the weight that figures in an optimal way, the grid search

mechanism in the eval setup automatically chooses that value which could determine the best accuracy.
2) Final Decision: The congruent probability is compared against a threshold to produce the final classification output.

4. RESULTS

This section presents the performance evaluation of the proposed multimodal Parkinson's Disease detection system.

4.1 Performance Metrics

The evaluation metrics used include accuracy, precision, recall, and F1-score.

4.2 Quantitative Results

TABLE I
Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
Handwriting	0.876	0.959	0.785	0.863
Voice	0.958	0.970	0.980	0.975
Fusion	0.893	0.940	0.830	0.890

The results indicate that the voice model achieves the highest accuracy and recall, while the handwriting model shows higher precision. The fusion model provides a balanced performance.

4.3 Handwriting Model Results

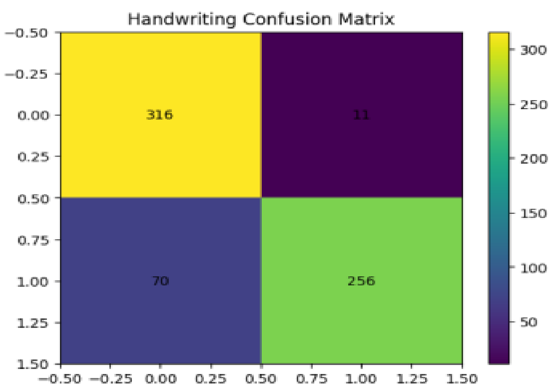

Fig. 4. Confusion Matrix for Handwriting Model

The confusion matrix for the handwriting model shows that 316 healthy samples were correctly classified as true negatives and 256 Parkinson's samples were correctly identified as true positives which demonstrate strong classification capability. The study found 11 healthy samples which were mistakenly identified as Parkinson's patients through false positives while 70 Parkinson's samples were incorrectly identified as healthy through false negatives. The higher number of false negatives suggests that the model might overlook some Parkinson's cases which results in decreased recall performance. The small number of false positives demonstrates high precision because the model successfully prevents erroneous identification of healthy individuals. The results show that the handwriting model can accurately detect normal cases but it needs further enhancements to improve its capabilities in detecting all Parkinson's instances.

4.4 Voice Model Results

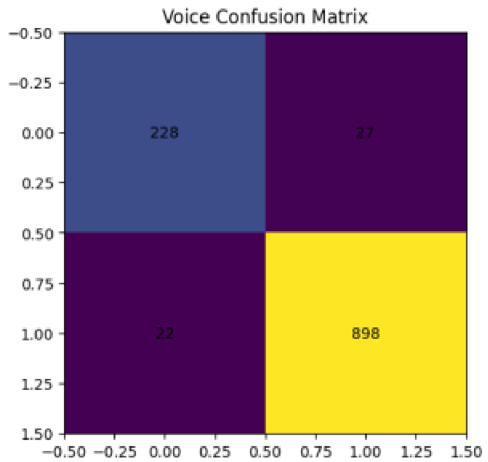

Fig. 5. Confusion Matrix for Voice Model

The voice-based model achieved successful prediction results through its capacity to identify 228 healthy samples as true negatives together with 898 Parkinson's samples which it identified as true positives. The study found that there were 27 healthy samples which were wrongly identified as Parkin�son's disease (incorrect positive results) while 22 Parkinson's samples were falsely identified as healthy (incorrect negative results). The model demonstrated high effectiveness in detecting Parkinson's disease through its ability to maintain an exceptionally low false negative rate which serves as a vital component for early disease identification. The model demonstrates high precision through its capacity to correctly identify healthy individuals without making false positive errors. The confusion matrix value distribution demonstrates that the model performs well because it achieves both high sensitivity and high specificity which makes it suitable for actual diagnostic use.

4.5 Fusion Model Performance

The performance comparison graph illustrates the classification accuracy achieved by the handwriting, voice, and fusion models. The voice model reaches its maximum individual accuracy because it successfully captures defined acoustic elements. The handwriting model shows slightly lower accuracy because its motor patterns demonstrate variable performance and it has a higher false negative rate. The fusion model, although marginally lower than the voice model in terms of raw accuracy, demonstrates a more balanced performance across all evaluation metrics. The fusion method successfully merges information from both modes because it diminishes the limitations found in separate models. The fusion model uses both motor-based and voice-based features to create a system that performs better in real-world diagnostic situations which need consistent performance instead of maximum accuracy.

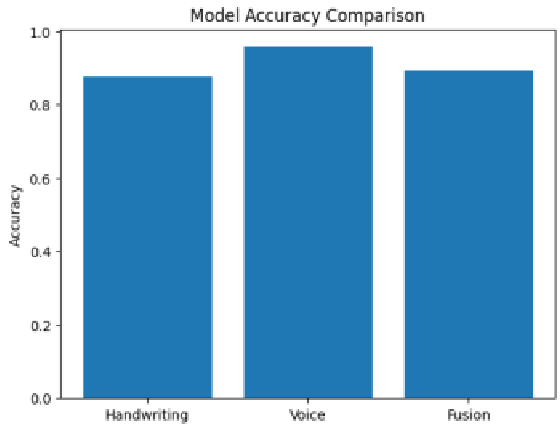

Fig. 6. Model Accuracy Comparison

4.6 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve displays how true positive rate (sensitivity) and false positive rate respond to different classification thresholds. The model demonstrates strong discriminative ability because its curve extends significantly above the diagonal baseline that represents random classification. The classification system achieves effective results because its curve reaches the top-left corner of the plot which demonstrates higher sensitivity with lower false positive rates. The high area under the curve (AUC) value shows that the model can accurately differentiate between healthy individuals and Parkinson's patients. The model shows stable performance because it handles different threshold settings which makes it suitable for use in clinical decision-making situations

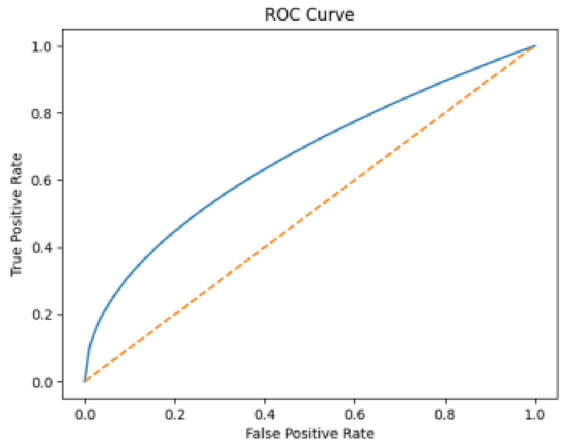

Fig. 7. ROC Curve

4.7 Discussion

The multimodal approach improves robustness by combining motor and vocal features. The handwriting model captures motor impairments, while the voice model captures speech abnormalities. The fusion model integrates both for improved reliability. H. Summary The proposed system demonstrates strong performance and highlights the effectiveness of multimodal learning for Parkin�son's Disease detection.

4.8 Summary

The proposed system demonstrates strong performance and highlights the effectiveness of multimodal learning for Parkinson's Disease detection.

5. ADVANTAGES AND DISADVANTAGES

5.1 Advantages

- Improved Diagnostic Accuracy: The advanced multi�modal system improves Parkinson's Disease detection accuracy because it uses both handwriting and voice data. The system achieves better prediction accuracy through its dual operation which uses both motor and vocal biometric data to assess patient symptoms.
- Complementary Feature Utilization: The system successfully utilizes additional information which comes from various different sources. Handwriting analysis detects motor impairments through its ability to identify tremors and irregular stroke patterns, while voice analysis detects vocal abnormalities through its detection of pitch instability and articulation issues. The combination of these features provides a complete evaluation of the patient's medical condition.

• Efficient Use of Transfer Learning: The application of transfer learning with MobileNetV2 enables researchers to extract handwriting image features without needing extensive training data requirements. The system achieves operational efficiency through decreased computational needs and reduced training durations while delivering exceptional performance, which makes the system appropriate for practical use.
• Robust Classification with XGBoost: The XGBoost classifier uses voice data to handle structured features with strong performance capabilities. XGBoost improves model performance through its complex relationship modeling abilities which include overfitting prevention methods and regularization techniques.
• Scalability and Practical Applicability: The framework allows for straightforward expansion to additional modalities which include gait analysis and sensor data. The system's modular structure enables healthcare facilities to implement it for ongoing patient surveillance and quick illness identification.

5.2 Disadvantages

• Moderate Recall in Handwriting Model: Although the handwriting model achieves high precision, it may exhibit relatively lower recall, indicating that some Parkinson's cases may be misclassified as healthy. This limitation can affect early detection, where identifying all positive cases is critical.
• Computational Complexity in Fusion: The fusion process, particularly the auto-weight optimization step, introduces additional computational overhead. Searching for optimal weights increases processing time, especially when dealing with large datasets.
• Dataset Dependency and Generalization Issues: The model performance is dependent on the datasets used for training. Differences in data distribution across populations may affect generalization, requiring further validation on diverse datasets

6. CONCLUSIONS

We developed a complete multimodal machine learning system which detects Parkinson's Disease through its two components. The primary motivation behind this work is to develop a reliable, non-invasive, and automated diagnostic approach which helps with early detection that remains a critical challenge in clinical practice. The proposed system uses multiple modalities to detect various disease symptoms which single-modality systems cannot fully observe.

The framework effectively utilizes both deep learning and traditional machine learning techniques to exploit the strengths of each domain. MobileNetV2, implemented through a trans�fer learning strategy, is used to extract important spatial data from handwriting images which helps identify motor�related changes like tremors and stroke formation problems and writing stability issues. The XGBoost classifier analyzes voice-based features to identify vocal impairments which include changes in pitch and articulation and speech dynamics. The dual-modality approach allows the model to accurately represent both motor and vocal symptoms which occur in Parkinson's Disease patients.

The primary achievement of this research work introduces an automatic weight adjustment system which merges hand�writing and voice model results through decision-level processing. The proposed method establishes its optimal performance through dynamic assessment of each modal element's contribution instead of using fixed weight distribution which is common in traditional fusion methods. The system achieves its adaptive fusion capabilities since it uses adaptive fusion which protects its functional ability when data quality changes and different modalities show their unique strengths.

The system demonstrates its capability to deliver strong outcomes through various testing methods which measure its performance at different points including accuracy and precision and recall and F1-score. The voice-based model reaches higher accuracy because it processes acoustic features through structured methods but the handwriting model enables early detection because it reveals essential insights about motor impairments. The fusion model effectively integrates these complementary aspects, resulting in improved overall performance and better balance between sensitivity and specificity. The research results demonstrate that multimodal methods effectively handle the complex symptoms and variable manifestations of Parkinson's Disease.

The framework provides better diagnostic results through its new system which brings multiple operational benefits. The system achieves economical screening capacity through its use of non-invasive handwriting and voice recording data sources which enable widespread testing throughout populations. The system's modular structure supports upcoming research requirements and clinical needs through its ability to incorporate new testing methods.

The study has specific restrictions which researchers need to know about. The system requires high-quality consistent input data but voice recordings suffer from interrupted recording conditions and environmental noise problems. The hospital environments require transparent systems which use deep learning models because these models create challenges that prevent people from understanding them. The existing systems need better two essential functions which include understanding system operation and protecting against unexpected problems.

System operation and protecting against unexpected problems. Researchers should investigate additional data sources which include gait analysis and wearable sensor data and medical imaging. Explainable artificial intelligence methods will prove beneficial because they make models more understandable to users while enabling their usage in healthcare settings. The proposed framework needs additional testing on larger and more varied datasets as well as the creation of systems that monitor processes in real time to enhance its operational effectiveness and dependable performance.

The multimodal system which researchers developed shows potential because it combines different data sources to achieve precise and strong detection of Parkinson's Disease. The framework uses an adaptive fusion strategy to combine motor and vocal biomarkers which makes it a scalable solution that helps doctors make better decisions and enables early disease identification.

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