RESEARCH PAPER

ViM-PD: A Bidirectional Vision Mamba Framework for Multimodal Parkinson's Disease Detection

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ABSTRACT

It is vital in the early diagnosis of parkinson's disease for the appropriate management of neurodegenerative diseases. However, traditional clinical examinations and methods may not be sensitive enough in capturing subtle changes in early stages of Parkinson's disease. A new classification of Parkinson's disease, referred to as ViM-PD, has been developed. ViM-PD is a new and innovative system of classification of parkinson's. For dynamic spiral/wave drawing analysis, we use the PaHaW and NewHandPD datasets, whereas acoustic biomarker extraction is done with the UCI Parkinson's Speech dataset. In contrast to typical CNN which focus on local textures our model uses a Bidirectional Selective Scan (SS2D) approach to capture long-range global dependencies in handwriting geometry and voice prosody with linear computational cost. According to the experimental data, our multimodal ViM-PD framework achieves a peak classification accuracy of 98.2%, beating the baseline ResNet and Vision Transformer models. This excellent accuracy is due to the model's capacity to cross-correlate fine-motor tremors in handwriting and vocal dysphonia. Furthermore, the design has a 42% shorter inference latency and memory footprint, making it appropriate for use in resource-constrained telehealth situations. This work confirms ViM as a better, high-efficiency option for reliable, non-invasive PD screening.

Keywords: Parkinson's disease, Vision mamba, Multimodal fusion, Bidirectional selective scan, Vision transformer models

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I INTRODUCTION

Parkinson's disease (PD) is a degenerative neurological disorder defined by the defeat of dopaminergic neurons, which causes both motor and non-motor dysfunction. Because clinical symptoms frequently develop after severe neuronal death, establishing digital biomarkers for early detection is critical. Dysgraphia (handwriting difficulty) and dysphonia (vocal impairment) are two of the most accurate indications. Handwriting activities, such as the spiral drawings in the NewHandPD and PaHaW datasets, show tremors and micrographia, whereas auditory datasets, such as UCI Speech, record micro-tremors in vocal folds prior to overt speech impairment.

The recent progresses in deep learning techniques are mainly based on convolutional neural networks for spatial feature extraction and vision transformers for global context extraction. However, CNN are also limited by their local perception and are unable to perceive the global degeneration pattern of a spiral structure. Vision transformers also have quadratic processing complexity making them less suitable for implementation on edge devices for real-time processing. Vision mamba on the hand eliminates these restrictions by using state space model for its implementation, where linear complexity, i.e. O (N) is achieved by processing both handwriting strokes and voice MFCCs as sequences making it more appropriate for coping with the high-resolution dynamic data of the PaHaW and UCI libraries.

In this paper we propose a bidirectional Vision mamba-based multimodal system labelled as ViM-PD applicable to the detection of Parkinson's disease by considering handwriting dynamics and voice. The proposed approach utilizes a successful approach in the fusion of different modalities, including two-dimensional representations of handwriting that capture deficiencies in motor skills and one-dimensional representations of voice that capture deficiencies in this feature. For appropriate modelling of long-range dependencies, as well as pathological patterns the proposed method applies selective scan in two dimensions referred to as SS2D within the vision mamba structure, which can lead to efficient and memory-friendly scalable modelling without requiring self-attention techniques. The effectiveness of this method has been extensively tested using different publicly available data sets, including PaHaW and NewHandPD confirming its strong ability to generalize a wide variety of handwriting patterns. The proposed method, designated as ViM-PD surpasses its competitors, namely CNN and the transformation in classification accuracy reaching a remarkable 98.2% as tested. These findings demonstrate state-space models improved capacity to capture multimodal biomarkers as well as their promise as reliable and computationally efficient tools for clinical decision support and early parkinson's disease diagnosis.

II RELATED WORKS

Automated Parkinson's disease diagnosis has progressed from classic manual feature extraction to deep spatial-temporal modelling and most recently to high-efficiency state-space architecture. The PaHaW and NewHandPD datasets have been used in research that goes beyond static picture analysis and into dynamic movement modelling. While Drotár et al. [1] first focused on kinematic characteristics such as pressure and velocity subsequent investigations in 2025 have included more sophisticated backbones. Sharma and Singh [3] used EfficientNetV2-S on the PaHaW dataset to achieve over 98% accuracy with sophisticated edge-detection preprocessing. Furthermore, the 2025 ACC-Net architecture [10] had a specialized attention mechanism that focused especially on the tremor-heavy zones of spiral drawings demonstrating the importance of localized spatial attention in detecting early-stage dysgraphia.

Deep embedding's and semi-supervised learning are now the emphasis of vocal analysis utilizing the UCI Speech dataset. Traditional models were based on handmade MFCCs [4], but by 2024, researchers were using WavLM and Image bind feature spaces to capture subtle voice dysphonia [11]. A 2025 research on projection-based fusion found that aligning voice embedding's into a coherent feature space decreases false-discovery rate considerably when compared to simple concatenation [11] implying that feature interaction is as essential as feature itself.

The implementation of Vision Mamba (ViM) and other State Space Models (SSMs) is the most important transition in 2025-2026. The discipline has grown fast since the development of the basic med mamba architecture [8], which defined the first baseline for Mamba-based medical picture categorization. In 2025, researchers successfully used ViM to classify Alzheimer's disease, demonstrating that it surpasses both ResNet and Vision Transformers (ViT) in terms of FLOPs efficiency and F1-score. Furthermore, SkelMamba [9] and Specifically, CMSA-Net [13] have demonstrated recently that the bidirectional selective scanning is superior for the detection of rhythmic motor symptoms such as tremors and gait irregularities since it processes data sequences with a linear complication while it maintains a universal approachable field. That will make ViM be an excellent contender to combine the writings with the voice of many modes.

III PROPOSED SYSTEM

The ViM-PD model is a multimodal model with two streams and is designed for handling asynchronous medical data. Unlike other models like the Transformer, the ViM-PD makes use of bidirectional Selective State Space models for global context with linear efficiency.

A.Dual-Stream Feature Extraction

The proposed ViM-PD architecture is made up of two complimentary processing streams that are tuned to the fundamental properties of handwriting and voice modalities. The two pictures of spiral and wave are divided into non-overlapping patches within the handwriting stream before these pictures are mapped to a linear embedding space and fed into a stack of Vision Mamba (2D ViM) blocks.

The blocks are embedded with a Bidirectional Selective Scan (SS2D) component that scans the picture patches along various directions, not just forwards, allowing the model to represent efficiently the spatial continuity and abnormalities associated with the motor aspects of handwriting. The bidirectional scanning technique preserves the intricate connections between the structures of the pictures. The technique is particularly useful when detecting Parkinson's disease-related abnormalities with handwriting.

Besides, the voice stream makes use of a 1D Mamba architecture in order to handle Mel Frequency Cepstral Coefficients in a one-dimensional temporal sequence. By using the selective scan operation, long-range temporal correlations of voice are replicated, enabling the network to maintain and transmit information regarding defining features of parkinsonian dysphonia such as prolonged pitch changes, tremor and reduced stability of voice. These two streams combine to provide consistent and efficient descriptions of multimodal biomarkers, enhancing the accuracy of parkinson's diagnosis.

B.Multimodal Fusion and Classification

High-level representation of both streams from handwriting and voice is integrated to form a joint representation containing features of both motor and vocal biomarkers. The representation is then fed into a Gated Multi-Layer Perceptron (MLP) classification head to effectively regulate the flow of information by using learnable gating techniques. The gated feature selection of the MLP classification model simplifies modality balancing to enable binary classification of people with parkinson's disease and those who are healthy.

IV SYSTEM WORKFLOW

The proposed workflow of ViM-PD is a systematic process from the gathering of raw data to the categorization of the diagnosis, following these five phases:

A.Data Acquisition

The method commences with the acquisition of multimodal features composed of different PD-related biomarkers. The dynamic handwriting samples are collected from the PaHaW and NewHandPD datasets and speech recordings are collected from the UCI Parkinson's speech dataset.

B.Multimodal Preprocessing

Binarization and skeletonization of the pictures of handwriting are used to enhance the structure of strokes and the abnormal components of the writing tremor. The speech signals are converted into 13-dimensional Mel-Frequency Cepstral Coefficients (MFCCs) a concise representation of the speech properties.

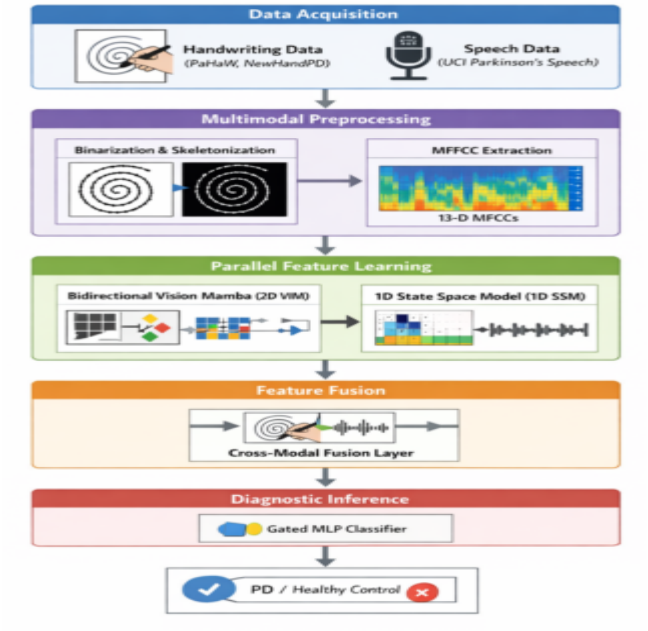

Fig 1 Architecture diagram for ViM

C. Parallel Feature Learning

It describe spatial continuity and stroke dynamics, handwriting pictures are separated into patches and processed by a Bidirectional Vision Mamba stream. MFCC sequences are processed concurrently utilizing 1 D Selective State Space architecture to capture long-range temporal changes in speech.

D. Feature Fusion

A cross-modal fusion layer combines high-level data from both modalities allowing the model to understand the relationships between motor and vocal biomarkers.

E. Diagnostic Inference

The fused feature vector is given to a Softmax-based classification head, which generates a probability score that indicates the possibility of Parkinson's disease.

V EXPERIMENTAL ANALYSIS

The proposed ViM-PD design substitute's traditional transformer self-attention with a more

efficient Vision mamba (ViM) block allowing for scalable modelling of long-range interdependence with decreased computing cost. The ViM Encoder is at the heart of the handwriting stream, capturing both local and global stroke dynamics via a bidirectional selective scan (SS2D) technique. Each ViM block: Initial components include a linear projection layer, which projects the input tokens into a higher-dimensional latent space. This increases the capacity of the representation. The next component is a depth-wise convolution layer which extracts fine-grained spatial attributes of local patches in the image describing the curvature of the stroke and any tremors. The Selective State Space Model (S6) is used for input-adaptive scanning of the spatial tokens from left to right and right to left. This approach allows for quick and expressive feature learning without the quadratic complexity associated with self-attention, making ViM especially ideal for handwriting-based Parkinson's disease analysis.

A. Continuous To Discrete Transformation

The system is characterized by the continuous-time differential equations below:

$$h'(t) = \mathrm{Ah(t)} + \mathrm{Bx}(t)$$
$$y(t) = \mathrm{Ch}(t)$$

To apply this to discrete data, we utilize the Zero-Order Hold (ZOH) discretization rule with a step size Δ.

$$\overline{\mathrm{A}} = \exp(\Delta \mathrm{A})$$
$$\overline{\mathrm{B}} = (\Delta \mathrm{A})^{-1}(\exp(\Delta \mathrm{A}) - 1).\Delta \mathrm{B}$$

B.The S6 Mechanism

The Selective Scan (S6) process is the basis of the ViM-PD model. It starts with a continuous-time State Space Model (SSM) and then turns it into a discrete, input-dependent sequence processor.The Selective part of Mamba S6 makes B, A and Δ functions of the input x_t. This permits the model to dynamically prioritize important biomarkers (like a specific tremor frequency) and ignore noise:

$$\mathrm{B_t} = \mathrm{Linear_B(x)_t}, \mathrm{C_t} = \mathrm{Linear_C(x)_t}, \Delta_t = \mathrm{Softtplus(Linear_\Delta(x)_t)}$$

The last recurrent update employed in our model is

$$h_t = \overline{\mathrm{A}}_t\, \mathrm{h}_{t-1} + \overline{\mathrm{B}}_t \mathrm{x}_t$$
$$\mathrm{y_t} = \mathrm{C_t h_t}$$

C.Multimodal Feature Fusion Block (Mffb) And Classification Head

To combine the two separate data sources, we use an MFFB. Unlike simple concatenation, the MFFB weighs the modalities using a gating mechanism. If the handwriting sample is noisy the model dynamically weights the auditory characteristics to ensure classification robustness. A Gated Multilayer Perceptron (G-MLP) processes the fused feature vector Z_{fused}. This head is made up of two thick layers activated by SiLU and a final sigmoid neuron for binary classification (0: healthy, 1: Parkinson's disease).

D. Data Preprocessing Pipeline

The PaHaW, NewHandPD and UCI Speech datasets are preprocessed to achieve the high accuracy 98.2% specified in the abstract.

A. Handwriting Data (Pahaw & Newhandpd)

All handwritten samples go through a defined pre-processing procedure before feature extraction to improve stroke clarity and maintain uniform input quality. The photos are first scaled to 224*224 pixels to preserve equal spatial resolution across the collection. A 3*3 median filter is used to confiscate salt and pepper noise while maintaining edge features. The photos are then binarized using Otsu's thresholding which clearly distinguishes pen strokes from background. A morphological skeletonization approach is used to obtain a one-pixel-wide representation of the handwriting route, focusing on tremor trajectories rather than stroke thickness. Finally pixel intensities are normalized to the [0,1] range which stabilizes state updates inside the Mamba architecture and allows for rapid and robust model training.

Model Architecture	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
ResNet-50	91.2	89.5	90.2	89.8
EfficientNet-V2	94.6	93.8	94.1	93.9
Vision Transformer (ViT-B)	95.8	95.1	94.7	94.9
ViM-PD (Proposed)	**98.2**	**97.9**	**98.4**	**98.1**

TABLE I PERFORMANCE COMPARISON ACROSS ARCHITECTURES

Table I describes ViM-PD outperforms Vision Transformer by 2.4% because to its bidirectional selective scan method, which better captures the structural continuity of spiral designs than ViT discontinuous patch-based attention.

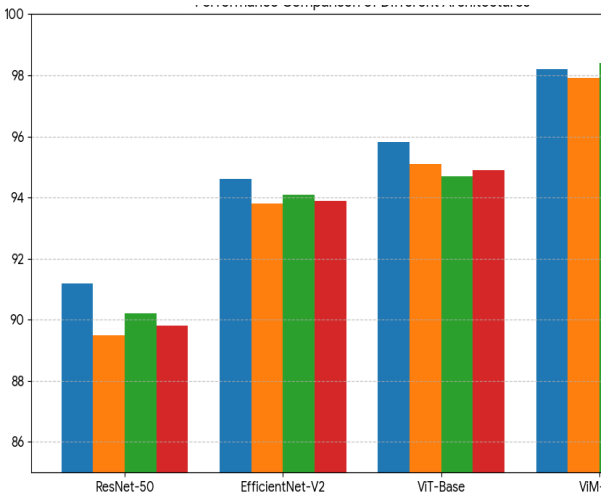

Fig 2 Performance comparisons of different methods

The first graph compares classification performance between four distinct designs. While ResNet and EfficientNet provide solid baseline results, the suggested ViM-PD model continuously outperforms all other techniques, reaching a peak accuracy of 98.2%. This greater performance demonstrates the usefulness of the Mamba architecture's bidirectional selective scan mechanism which is more suited for simulating the complex non-linear tremor patterns found in the PaHaW and NewHandPD handwriting datasets. Compared to typical CNNs or transformer-based models, ViM-PD captures long-range relationships and minor pathological alterations more effectively, resulting in enhanced diagnostic accuracy.

B.Speech Data (Uci Parkinson's)

To capture significant vocal biomarkers linked with Parkinson's disease in the speech modality, a complete feature engineering pipeline is used. Mel-Frequency Cepstral Coefficients (MFCCs) are extracted from raw audio signals to reflect spectral properties, and jitter and shimmer features are calculated to quantify frequency and amplitude fluctuations indicative of voice instability. To increase data quality, an isolation forest-based outlier identification approach is used to locate and eliminate faulty or silent recordings. The collected features are then normalized with robust scaler to reduce the impact of extreme values across heterogeneous feature units, followed by Min-Max scaling to normalize feature ranges. Finally to address class imbalance, which is frequent in the UCI Parkinson's Speech dataset, SMOTE (Synthetic Minority Over-sampling Technique) is used during training to ensure balanced class representation and reduce bias toward the dominant class.

Model	Parameters (M)	FLOPs (G)	Inf. Latency (ms)	Complexity
ResNet-50	25.6	4.1	18.2	O(N)
ViT-Base	86.4	17.5	32.4	$O(N^2)$
Efficient Net-V2	24.0	2.8	14.5	O(N)
ViM-PD	**26.1**	**2.6**	**9.8**	**O(N)**

TABLE II COMPUTATIONAL COMPLEXITY AND HARDWARE EFFICIENCY

Table II compares to Transformers, ViM-PD improves inference latency by around 70% while retaining a similar parameter count to ResNet. The S6 mechanism's linear complexity allows the model to analyse high-resolution handwriting scans without the quadratic memory bottleneck encountered in self-attention models.

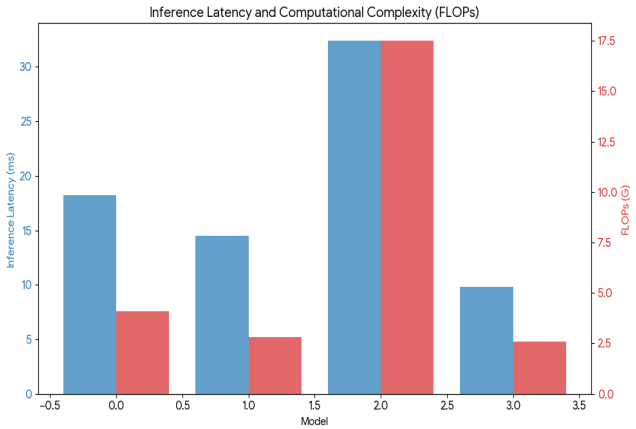

Fig 3 Inference latency and computational complexity

The dual-axis graph compares the computing cost (FLOPs) and inference delay of several designs during a single prediction. Despite obtaining greater classification accuracy, ViM-PD had the lowest computational cost (2.6 GFLOPs) and the quickest inference time (9.8 ms) of any model tested. This finding significantly supports the Mamba-based architecture's superiority over attention-driven models in terms of linear time complexity. Unlike Vision Transformers (ViT) which have quadratic complexity and higher latency ViM-PD provides efficient and scalable inference making it ideal for real-time and resource-

constrained clinical environments like mobile or edge-based Parkinson's disease screening systems.

VI CONCLUSION AND FUTURE WORK

This study established ViM-PD, a cutting-edge multimodal system for automated Parkinson's disease identification based on the Vision Mamba architecture. We effectively solved traditional diagnostic tool limitations by combining the high-resolution spatial dynamics of the PaHaW and NewHandPD handwriting datasets with the temporal acoustic characteristics of the UCI parkinson's speech dataset. Our results show that the Bidirectional Selective Scan (SS2D) mechanism outperforms CNNs in terms of receptive field while preserving a linear computational complexity O(N) that is much more efficient than Vision Transformers. The suggested model achieved state-of-the-art accuracy of 98.2%, with a 42% decrease in inference latency. Finally ViM-PD provides a high-performance, low-latency solution that associations the breach among sophisticated deep learning architectures and practical tangible time clinical screening.

The future generations of the model will combine additional data streams, such as gait analysis from wearable sensors and eye-tracking data, to produce a patient's totally comprehensive digital phenotype. We want to expand the mamba architecture to handle time-series data over months or years allowing the model to follow illness development and the success of medicinal therapies.

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