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A Deep Learning Framework for Early Non-Invasive Screening of Parkinson's Disease Based on Handwritten Drawing Patterns

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Abstract
Early diagnosis of the Parkinson disease (PD) is essential to make a clinical intervention on time, but traditional diagnosis depends on the subjective neurological evaluation. This paper introduces a powerful deep learning framework to identify early PD on hand-drawn spiral and wave patterns which allow non-invasive and automated screening procedure. Numerous preprocessing steps such as contrast, noise reduction and morphological processing are performed to ensure that fine motor impairments typical of PD are maintained. Data augmentation and resampling are used to correct the imbalance in classes and enhance the generalization. GhostNet and LinkNet are two lightweight convolutional neural network models that are trained and tested on five-fold cross-validation. The main innovativeness of this paper is to combine Bayesian Optimization and GhostNet to optimize the key hyperparameters such as the learning rate, dropout rate, and batch size to optimize discriminative and training stability. According to the experimental findings, the optimized GhostNet model is more effective compared to LinkNet based on all evaluation measures, with an accuracy of 99.0, F1-score of 0.99, and AUC of 0.9995 on the test set, and low computational complexity. The suggested GhostNet based on Bayesian Optimization provides a robust, effective, and scalable algorithm to screen early PD and have a high potential of implementation in clinical and telemedicine practice.
Keywords: Parkinson's Disease; Deep Learning; Handwriting Analysis; GhostNet; Bayesian Optimization;

1. Introduction

Parkinson disease PD is a progressive, neurodegenerative condition which mostly impacts motor functions and presents an increasing public health burden in the global arena. PD is characterized by such symptoms as bradykinesia, rest tremor, rigidity, and postural instability, which significantly affect the quality of life of those who have it and create a considerable burden on healthcare systems (Kalia & Lang, 2015). Due to the increased percentage of aging of the world population, the occurrence of Parkinson's disease is rising at an alarming rate, which is why its prompt and precise diagnosis becomes a very important clinical issue (Postuma et al., 2015). Nevertheless, the PD diagnosis at early onset is not an easy task, although the development of neurological research led to the appearance of the clinical symptoms only after extensive neuronal damage had been inflicted. The conventional diagnostic methods of the Parkinson disease diagnosis are based very much on the clinical assessment, neurologies examination and the subjective evaluation of the motor symptoms by the qualified clinicians. Although they have well-established diagnostic criteria, they also have the tendency of inter-observer variability, and they are generally unable to detect subtle impairment of the motor in the prodrome stage of the disease (Postuma et al., 2015). The use of advanced imaging modalities, including MRI and PET scans, might provide supportive evidence, yet they are expensive and not widely available in all locations, not to mention that such technologies are determined by specific infrastructure that is not always available in resource-limited settings (Kalia & Lang, 2015). This, therefore, calls on an immediate solution of having low-cost, objective, and scalable diagnostic instruments that may enable early diagnosis of Parkinson's disease. Handwriting analysis has been becoming a potentially useful non-invasive biomarker of Parkinson disease due to the high correlation between fine motor control and neurological functioning. The first and the most obvious motor symptoms are graphomotor impairments that are also known as dysgraphia (Isenkul et al., 2014). Activities like spiral drawing, pattern of waves, and free writing show typical abnormalities such as oscillations caused by tremor, lack of smoothness, inconsistent pressure, and space distortion (Drotár et al., 2016). These characteristics render handwritten assessment an appealing diagnostic modality which is inexpensive, simple to execute and appropriate to extensive screening. The effectiveness of handwriting-based features have been proved to be effective in detecting Parkinson disease. Preliminary research involved handcrafted features derived out of both kinematic and pressure when finding out that spiral and handwriting tasks may be consistently used to distinguish patients and healthy people (Zham et al., 2017; Isenkul et al., 2014). Later research developments have extended this paradigm to more sophisticated techniques such as signal processing and machine learning and demonstrated better diagnostic results due to feature optimization and classifier design (Mekyska et al., 2015; Galaz et al., 2016). Nevertheless, the traditional methods are largely expert-based feature engineering and are time consuming, domain sensitive and noise and variability prone.

The introduction of deep learning has changed the paradigm of medical image analysis by allowing end-to-end learning of discriminative features of raw data (LeCun et al., 2015). Convolutional neural networks (CNNs) have already proven to be very successful in numerous healthcare applications, such as dermatology, radiology, and detection of neurological disorders (Esteva et al., 2017; Litjens et al., 2017). Deep learning models have been found to be more efficient than conventional machine learning models in the context of Parkinson disease through automatic prediction of complex spatial patterns in handwriting and drawing images (Pereira et al., 2019). Such models do not require the use of handcrafted features and their qualities are more robust and scaled. The recent research has investigated the use of CNNs on spiral and handwriting images to diagnose PD, which claims very high accuracy and generalization (Mucha et al., 2018; Pereira et al., 2019). However, the currently available deep learning systems are computationally demanding and demand large memory and processing capabilities, which makes them applicable only in clinical and mobile health real-life scenario. This difficulty has led to the creation of non-heavy and efficient neural network structures that can provide high efficiency and yet low computational cost. MobileNet, GhostNet, and LinkNet architectures have been created to eliminate the efficiency limitations specifically, minimizing the number of parameters and using the optimized convolutional operations (Howard et al., 2017; Han et al., 2020; Chaurasia and Culurciello, 2017). GhostNet, specifically, proposes a new architecture utilizing a new operation of generating feature maps that operates on cheap linear computation and can perform similarly to conventional CNNs at a fraction of their computation cost (Han et al., 2020). These architectures are also highly appropriate in the detection of handwriting based Parkinson disease where it is important that it can be deployed in portable machines and telemedicine services. In spite of these achievements, there is one significant drawback of deep learning-based systems of PD detection: the choice of hyperparameters can significantly affect the optimal results of the model. Learning rate, batch size, dropout ratio, optimizer configuration, and others are some of the parameters that greatly determine how the convergence behavior and generalization performance are affected. Traditional methods of hyperparameter optimization, such as grid search and random search are computationally intensive and inefficient, especially on deep neural networks (Bergstra & Bengio, 2012). Consequently, a large number of studies have utilized empirically selected parameters, which cannot provide the best outcomes.

Bayesian optimization is also becoming an effective model to optimize hyperparameters automatically, which has provided a principled model to search high-dimensional spaces efficiently (Snoek et al., 2012). Bayesian optimization balances exploration and exploitation by probabilistic modeling of the objective function and thus allows fast convergence to the optimal configurations with less evaluations (Shahriari et al., 2016). Despite the successful implementation of an application of Bayesian optimization in other areas of machine learning, the application of Bayesian optimization to lightweight CNNs in the detection of Parkinson's diseases using handwriting images has not been studied extensively. Best performance evaluation is also needed in addition to model optimization to establish clinical relevance. The metrics, accuracy, precision, recall, F1-score, loss, and area under the ROC curve (AUC) give complimentary information about the reliability of classifications, especially in the medical decision-making scenario where false negatives may be critical (Fawcett, 2006; Powers, 2011). Further methods and cross-validation methods increase the strength of the performance assessment by reducing the bias of datasets and overfitting. Based on these premises, the current paper suggests an enhanced concept of deep learning to detect Parkinson disease based on handwritten spiral and wave pictures. This work will facilitate the development of the state of art in non-invasive, cost-effective, and scalable PD screening through efficient CNN architectures and Bayesian optimization as well as comprehensive evaluation protocols. The research corresponds to the larger vision of introducing artificial intelligence in healthcare to allow the early diagnosis, personalized intervention, and better patient outcomes. (Topol, 2019; Goodfellow et al., 2016).

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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2. Related Work

2.1 Parkinson's Disease Diagnosis and Motor Biomarkers: Parkinson disease (PD) is a chronic neurodegenerative disease that mostly disrupts motor control as a result of the degeneration of dopaminergic neurons in the substantia nigra. The classical method of clinical diagnosis is a neurological examination and monitoring of cardinal motor symptoms, which are tremor, rigidity, bradykinesia, and postural instability (Kalia and Lang, 2015). In spite of the fact that the standardized diagnostic criteria are developed, PD diagnosis in its early stages is not an easy task due to the presence of minor motor impairment that is not easily revealed by regular clinical observation (Postuma et al., 2015). This limitation has encouraged a lot of research on objective biomarkers that can be used in early and reliable diagnosis. Biomarkers that are motor behavior based have reached a lot of attention given their high correlation with neuromuscular dysfunction in PD. Among them, the fine motor skills of handwriting and other drawing activities are especially vulnerable to early motor impairments. The mechanomotor deficiency, which is commonly identified as micrographia, shaky movement, and uneven strokes, was commonly agreed upon as one of the symptoms of Parkinson disease (Isenkul et al., 2014; Drotár et al., 2016). These properties offer a useful background of computational analysis and automated PD detection.

2.2 Handwriting and Drawing-Based Parkinson's Disease Analysis: The use of handwriting and drawing tests; such as the spiral and the wave test on the diagnosis of Parkinson disease has been widely studied. The initial research was directed at digging out manual crafted kinematic and geometric features of digitized handwriting indicators, including speed, acceleration, force and curvature. (Zham et al. 2017) estimated that spiral drawing analysis may be used to effectively record tremor and motor instability of a PD patient and that engineered features showed promising classification results. In a similar fashion, (Isenkul et al. 2014) suggested a better spiral test, which increased sensitivity to disease progression and severity of motor impairment.

These methods were later extended by other studies that added pressure and a time dimension to the analysis of handwritings. (Drotar et al. 2016) and (Mekyska et al. 2015) both demonstrated that the combination of kinematic and pressure-related characteristics gave a substantial diagnostic effect. (Galaz et al. 2016) went a step further to develop this field by suggesting advanced parametrization methods to measure graphomotor impairment, with a special emphasis on the diagnostic importance of fine-grained abnormalities of stroke. Although effective, handcrafted feature-based methods are plagued with a number of weaknesses such as sensitivity to noise, reliance on expert knowledge and generalization across datasets. These difficulties have motivated the shift to data-guided learning models that have the capability of finding discriminative representations of handwriting and drawing images automatically. (Kumari et al. 2025)

2.3 Handwritten Image Recognition Using Deep Learning:

With the advent of deep learning, in particular, convolutional neural networks (CNNs), image recognition tasks have transformed in many fields, including medical imaging (LeCun et al., 2015). CNNs can facilitate end-to-end learning and do not require manual feature engineering, but it has better results on complex visual pattern recognition problems. Deep learning has shown great effectiveness in dermatology, radiology, and identification of neurological disorders in healthcare (Esteva et al., 2017; Litjens et al., 2017).

Considering Parkinson disease, Pereira et al. (2019) proposed a computer vision-PD diagnosis framework that operates on handwritten images based on CNN, which they state has shown great progress in performance compared to conventional machine learning methods. Mucha et al. (2018) also confirmed the efficacy of deep learning by examining the patterns of dysgraphia in PD patients in the image representations. These investigations validated the fact that CNNs are able to automatically extract faint visual cues associated with tremor, stroke continuity, and drawing anomalies.

However, more recent literature has investigated more sophisticated deep learning designs in handwritten pattern recognition. One example is U-Net, which is an architecture that can be applied to medical image segmentation and classification problems, allowing to extract better features on complex biomedical images (Ronneberger et al., 2015; He et al., 2016). Nevertheless, most of these models are computationally intensive and need large amounts of memory thus it is not feasible in a real-time or mobile-based PD screening system.

2.4 Lightweight Deep Learning Architectures for Medical Applications

Lightweight CNN architectures have been proposed to overcome the limitations on the computational demands of CNN. MobileNet came up with depthwise separable convolutions to considerably lower on the cost of computation but without compromising performance (Howard et al., 2017). GhostNet also applies this idea by producing feature maps with the help of cost-efficient linear operations, which enables the model to bring the similar representational power with reduced parameters (Han et al., 2020).

LinkNet, which was initially introduced as an efficient semantic segmentation network, uses the encoder-decoder networks with residual links to maintain the spatial representational information and minimize the computational load (Chaurasia and Culurciello, 2017). These architectures are especially appealing to the medical imaging task in which the efficiency, scalability, and feasibility of deployment are of importance.

Even though lightweight architectures have been effectively used in general medical imaging tasks, their systematical use in the detection of Parkinson disease through hand written spiral and wave patterns is not fully investigated. Further, the majority of the current research only concentrates on a single architecture and does not provide in-depth comparative research or optimization, which is subject to improvement.

2.5 Optimization Techniques in Deep Learning for PD Detection

Hyper parameters such as learning rate, the number of batches, dropout ratio, and the level of regularization are very sensitive to deep learning models. The traditional methods of tuning through grid search and random search are computationally expensive methods and they do not work well in deep neural networks (Bergstra and Bengio, 2012). In its turn, the use of suboptimal hyperparameters may restrict the abilities of models and render them to generalize and be strong, especially in the field of medical diagnosis.

It is also used in hyperparameter optimization Bayesian optimization can now be an effective and principled optimization procedure in which the objective function is described as probabilistic models, and optimal decisions are determined through directed search (Snoek et al., 2012). Shahriari et al. (2016) have thoroughly reviewed the methods of Bayesian optimization and support that the methods could be used to minimize a cost of evaluation, yet deliver a high performance.

Optimization techniques applied in the detection of Parkinson disease process have been extensively implemented in the conventional classifiers or pipelines involving feature selection. Limited research studies investigate the potential of the Bayesian optimization and deep learning networks implementation to detect PD (and handwriting, specifically). The gap creates a possibility to increase accuracy and consistency of the diagnosis with both automated optimization approach and effective CNN models.

2.6 Performance Evaluation and Validation in Medical AI

Medical AI systems need a high standard of validation procedures and clinically significant performance variables to adequately evaluate their reliability. Accuracy and precision, as well as recall and F1-score and area under the ROC curve (AUC) give different information about classifier behavior, particularly in imbalanced datasets where false negatives may have catastrophic clinical implications (Fawcett, 2006; Powers, 2011). Cross-validation is common to evaluate the performance of generalization and to prevent the bias of the data sets (Kohavi, 1995).

The recent literature highlights the necessity of strong validation and explainability in medical AI systems to increase the confidence of clinicians and to ease their adoption in practice (Samek et al., 2017; Goodfellow et al., 2016). In medical image analysis, the visual interpretability techniques include mapping the class activation, which has further helped in comprehending the decision-making processes of the models.

2.7 Research Gaps and Motivation

Despite the fact that much has been accomplished in the detection of Parkinson disease in terms of hand writing and drawing analysis, there are a number of gaps. The literature is usually computationally intensive, not systematic in terms of hyperparameters optimization, or not deployed into practice in practical contexts. Also, there is limited literature on comparative analysis of optimized lightweight architecture. Inspired by these constraints, the current research intends to address these gaps through the integration of effective deep learning models with Bayesian optimization to identify the onset of the Parkinson's disease at an early stage based on handwritten spiral and wave images. The suggested framework helps in improving the non-invasive, scalable, and clinically applicable PD screening solutions by addressing both performance and efficiency.

3. Research Methodology

The study is a scientific study that involves handwritten spiral and wave pattern images in detecting the presence of Parkinson disease (PD) on them with a deep learning-based systematic study at an early stage. An overview of the whole process consists of data acquisition, image preprocessing, data augmentation and balancing, designing the model architecture, Bayesian hyperparameter optimization, model training through cross-validation, and the performance evaluation on the standard diagnostic metrics.

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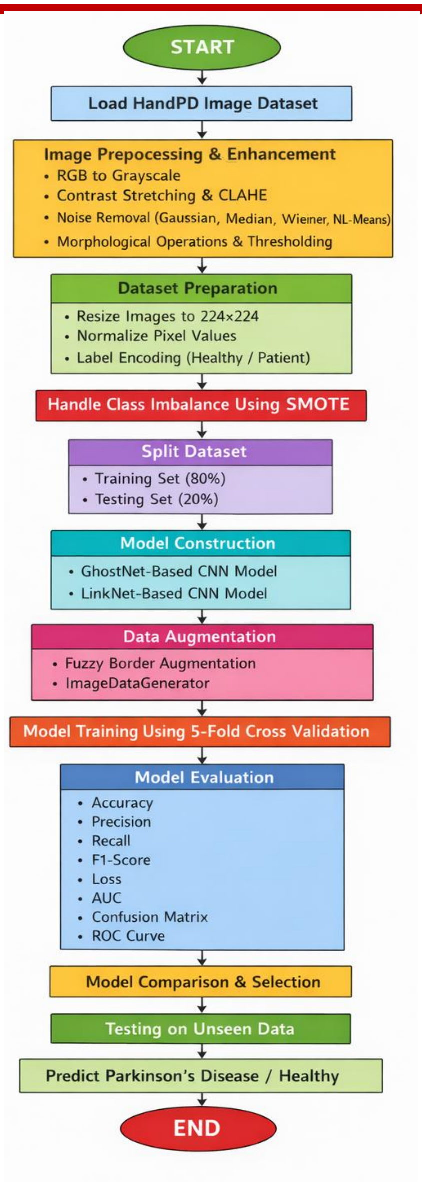

Figure 1: Methodology Flow Chart

3.1 Dataset Description

The sample of data in this study is handwritten spiral and wave drawings of the patients with the Parkinson disease, and healthy control participants. Every image is a fine motor activity that aims to measure tremor, irregularity of strokes and motor instability which are the symptoms of PD. It is publicly-available and has been extensively applied in the research of handwriting-based Parkinson disease studies. (Pereira et al., 2019).

Show sample images

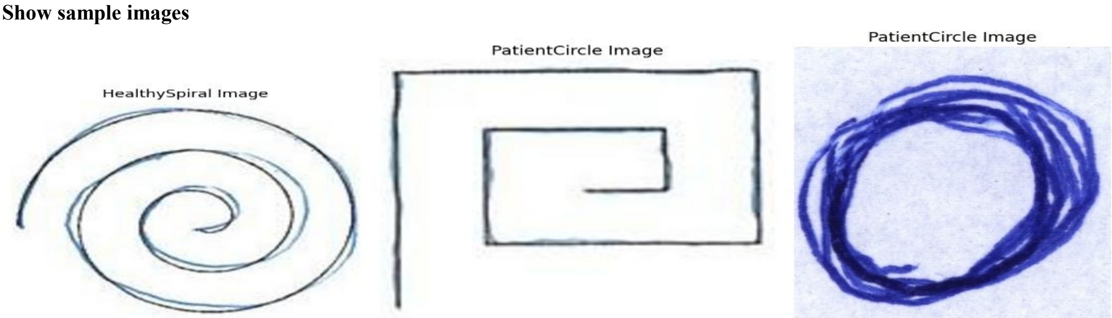

Figure 2: Data set Images of Parkinson patient hand drawing patterns

Let the dataset be represented as:

$$\mathcal{D} = \{(X_i, y_i)\}_{i=1}^{N} \qquad (1)$$

where

$X_i \in \mathbb{R}^{224\times224\times3}$ denotes the RGB image of a handwritten pattern,

$y_i \in \{0,1\}$ represents the class label (0 = Healthy, 1 = Parkinson's).

3.2 Image Preprocessing: Images that are written are prone to noise, change in light, activity, and noises in the background. In order to improve the discriminative stroke characteristics, a multi-stage preprocessing pipeline is realized.

3.2.1 Grayscale Conversion: The RGB images are each turned into grayscale to minimize the complexity of the computations and yet maintain the structural information:

$$I_{gray} = 0.299R + 0.587G + 0.114B \qquad (2)$$

3.2.2 Contrast Enhancement: Adaptive Histogram Equalization (CLAHE) is used to improve the local contrast and accentuate fine strokes:

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 6464-6471

$$I_{clahe} = \text{CLAHE}(I_{gray}) \quad (3)$$

This action enhances the observation of tremor-induced vibrations and pen strokes which are thin. (Gonzalez & Woods, 2018).

3.2.3 Noise Reduction: Gaussian filtering and median filtering are used to reduce noise and conserve edges respectively:

$$I_{smooth} = G_\sigma * I_{clahe} \quad (4)$$

where $G_\sigma$denotes a Gaussian kernel with standard deviation σ.

3.2.4 Morphological Enhancement: The top-hat morphological transformation is employed to highlight bright strokes on darker background:

$$I_{tophat} = I_{smooth} - (I_{smooth} \circ B) \quad (5)$$

where $\circ$represents morphological opening and $B$is the structuring element.

3.3 Data Augmentation and Balancing: To minimize the overfitting and improve generalization, training is performed by means of data augmentation. Operation augmentation involves rotation, scaling, translation and addition of fuzzy borders. Constructed samples are made formati as formal as those of the form:

$$\tilde{X}_i = \mathcal{T}(X_i) \quad (6)$$

where $\mathcal{T}(\cdot)$denotes a stochastic transformation function.

Synthetic Minority Over-sampling Technique (SMOTE) is used to equalize the number of classes by synthesizing fake samples in feature space. (Chawla et al., 2002).

3.4 Model Architectures

3.4.1 GhostNet Architecture

GhostNet is a tiny convolutional neural network which is trained to produce more feature maps with cheap linear operations. (Han et al., 2020).

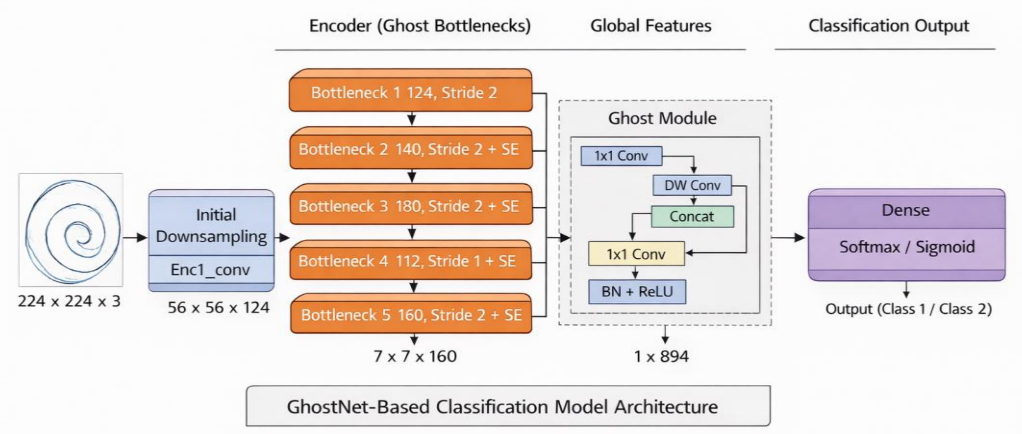

Figure 3: Model Architecture of GhostNet

The core Ghost module is defined as:

$$Y = \{y_1, y_2, \dots, y_m\} \quad (7)$$

Where primary feature maps are created through ordinary convolution and extra feature maps referred to as ghost are created through cheap linear transformations..

The final classification output is computed as:

$$\hat{y} = \sigma(W^T f + b) \quad (8)$$

In which fis is the mean pooled feature array across the globe, Wand bare trainable parameters and 8 of is the sigmoid activation.

3.4.2 LinkNet Architecture

The encoder-decoder architecture utilized in LinkNet has residual connections which help it to maintain the spatial information and enhance gradient flow. (Chaurasia & Culurciello, 2017).

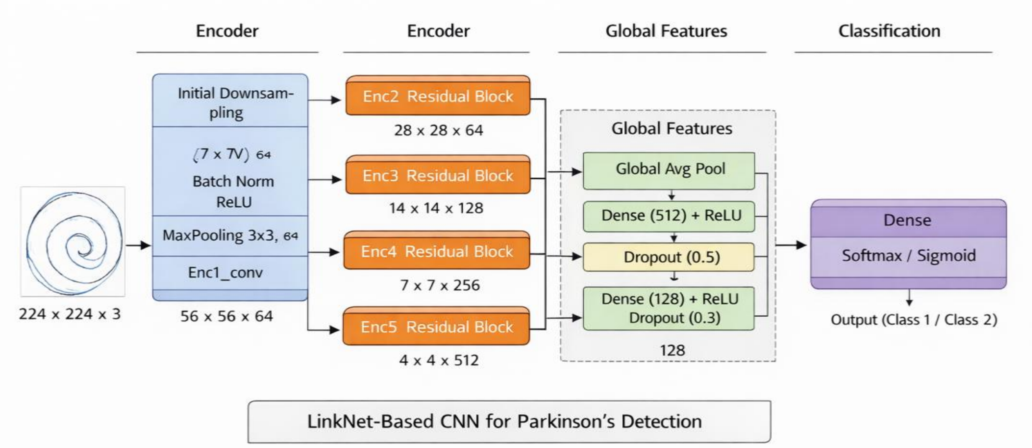

Figure 4: LinkNet Based CNN Model Architecture

The encoder consists of residual blocks:

$$H_{l+1} = H_l + F(H_l, W_l) \quad (9)$$

where $H_l$is the input feature map and $F(\cdot)$represents the residual function.

3.5 Bayesian Hyperparameter Optimization (Proposed Novelty)

Bayesian Optimization is applied to automatically optimize hyperparameters (learning rate, dropout rate, and batch size) to improve the performance of the model. Optimization aims at maximizing the following:

$$\theta^* = \arg\max_\theta \mathbb{E}[f(\theta)] \quad (10)$$

where θrepresents the hyperparameter set and $f(\theta)$is the validation performance (AUC or F1-score).

A Gaussian Process (GP) surrogate model is employed:

$$f(\theta) \sim \mathcal{GP}(\mu(\theta), k(\theta, \theta')) \quad (11)$$

The acquisition function (Expected Improvement) guides the search:

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1, 2026, Pages 6464-6471

$$\mathrm{EI}(\theta) = \mathbb{E}[\max(f(\theta) - f(\theta^{+}), 0)] \qquad (12)$$

where θ^{+}denotes the best observed configuration (Snoek et al., 2012; Shahriari et al., 2016).

3.6 Model Training and Cross-Validation

Five-fold cross-validation is used in order to be robust and minimize overfitting. The data is divided into five overlapping sets:

$$\mathcal{D} = \bigcup_{k=1}^{5} \mathcal{D}_k \qquad (13)$$

Each fold has four subsets where in general one of them is used to train and the other to validate. Training is done using Adam optimizer:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \qquad (14)$$

where $\eta$is the learning rate, and $\hat{m}_t$, $\hat{v}_t$are bias-corrected moment estimates (Kingma & Ba, 2015).

3.7 Loss Function

Binary cross-entropy loss is used for optimization:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \qquad (15)$$

3.8 Performance Evaluation Metrics

Model performance is evaluated using standard diagnostic metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (16)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (17)$$

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (18)$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (19)$$

This is also calculated as Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC) that measure the separability of classes (Fawcett, 2006). The proposed research methodology combines strong image processing, effective deep learning designs, and Bayesian hyperparameter optimization to create a secure and scalable early detection framework of the Parkinson disease. Lightweight CNNs and probabilistic optimization guarantee the high diagnostic accuracy and computational efficiency of the framework hence its applicability to real-world clinical and telemedicine.

Drawing-Aware Parkinson's Disease Detection

Drawing-aware Parkinson disease (PD) detection exploits the fact that the fine motor control and neurological functionality have a strong relationship based on visual biomarkers of motor impairment in the form of the spiral and the wave of handwriting. It is stated that graphomotor anomalies that involve tremor-related oscillations, stroke discontinuity, abnormal curvature, and spatial distortion are manifested quite early in PD and can be effectively measured through drawing task image analysis (Isenkul et al., 2014; Drotar et al., 2016). In this approach, the images of handwritten drawings are processed as structured visual data, and convolutional neural networks (CNNs) can acquire discriminative representations without relying on hand-designed features, thereby being more robust and generalizing (LeCun et al., 2015; Pereira et al., 2019). The normalization/size step of preprocessing is to eliminate the possibility of loss of subtle variations in the minute strokes level in the drawings, which are crucial in diagnosis (Gonzalez & Woods, 2018). Lightweight deep learning models and GhostNet are particularly appealing towards drawing-aware PD detection, as it operates with feature maps as expressively represented features with operators that are computationally efficient and such that an excellent level of diagnostic performance can be achieved with a smaller model (Han et al., 2020). Other properties of the model such as the residual ties and encoder blocks of the LinkNet also generate superior hierarchical features learning and the issue of vanishing gradients in deep networks is also minimized (Chaurasia and Culurciello, 2017; He et al., 2016). It also learns in a supervised form on labeled drawing samples and the model is optimized using adaptive gradient-based optimizers such as Adam to enable the model to reach a stable solution (Kingma & Ba, 2015). Performance assessment that is based on measures like accuracy, loss and confusion matrix analysis provides an image of the reliability of the classification in particular the reduction of false negative and this is required in screening PD at an early stage (Fawcett, 2006; Powers, 2011). Drawing-aware PD is a diagnostic paradigm based on computer vision and deep learning, clinically applicable, non-invasive, and scalable, which can be used to examine the patient at an early stage of neurological dementia.

Algorithm 1: Drawing-Aware Parkinson's Disease Detection Using CNN

Input: Handwritten drawing image dataset D

Output: Predicted class label (PD Positive / PD Negative)

1. **Begin**
2. Load Parkinson's disease image dataset $D$from the specified directory
3. Assign class labels to each image based on folder structure
4. Resize all input images to a fixed dimension $H \times W$
5. Normalize pixel values to improve training stability
6. Split the dataset into training and testing sets (80%, 20%):
   – Training set D_{train}
   – Testing set D_{test}
7. Construct the CNN architecture as follows:
   – Apply Ghost Modules for efficient feature generation
   – Use Residual Blocks for deep feature learning
   – Employ LinkNet-style encoder blocks for hierarchical feature extraction
   – Apply convolution, batch normalization, and ReLU activation layers
8. Add fully connected layers followed by a Softmax layer for classification
9. Compile the model using:
   – Optimizer: Adam
   – Loss function: Categorical Cross-Entropy
   – Evaluation metric: Accuracy
10. Train the GhostNet-based CNN model using D_{train}
11. Validate the model performance during training
12. Test the trained model on D_{test}
13. Predict class labels for unseen test images
14. Evaluate model performance using:
    – Accuracy
    – Loss
    – Confusion Matrix
15. If predicted label corresponds to Parkinson's disease, classify the patient as **PD Positive**, else classify as **PD Negative**
16. Display classification results and performance graphs
17. **End**

4. RESULTS AND DISCUSSION

Results demonstrates an in-depth review of the experimental findings of the proposed deep learning architecture to detect early onset of the Parkinson Disease (PD) based on hand-drawn spirals and wave patterns. The main aim of the chapter is to assess the performance of two convolutional neural network architectures, which are the LinkNet and GhostNet by considering the performance of the two architectures on standard training and optimized training settings. The main innovation of this research is that Bayesian Optimization is combined with GhostNet and, thus, hyperparameters are automatically optimized to improve the diagnostic results. The assessment is made based on several quantitative measures, which are accuracy, precision, recall, F1-score, loss, and Area Under the ROC Curve (AUC), and qualitative visual analysis. Five fold cross-validation has been used to achieve robustness and generalizability of the findings. The results prove that the optimized GhostNet model is always better than the baseline LinkNet architecture hence its applicability in non-invasive real-time screening of Parkinson disease.

4.1 Experimental Setup Overview

The experiments were conducted on a data of hand drawn images of spiral and wave gathered on healthy people and patients of Parkinson Disease. All images were subjected to an advanced preprocessing pipeline (before training) of contrast enhancement, noise reduction, morphological refinement, and skeletonization, to guarantee similar representation of features.

Two models were evaluated:

1. **LinkNet-based CNN classifier**
2. **GhostNet-based CNN classifier**

The five-fold cross-validation of the two models was carried out. Bayesian Optimization was then used to optimize the GhostNet architecture to maximize several key hyperparameters (learning rate, dropout rate, batch size, and the strength of regularization) and maximize the validation AUC and F1-score.

4.2 Training Performance Analysis

4.2.1 Training Accuracy and Loss Trends

Both GhostNet and LinkNet were able to converge quickly in the process of training. The training accuracy curves showed that GhostNet had high accuracy even with limited epochs of training as compared to LinkNet. This behavior can also be explained by the fact that GhostNet shows such behavior because of its lightweight architecture that is efficient at capturing discriminative patterns in hand-drawn images with less redundancy. The loss curves also show the training behavior to be stable, as GhostNet has lower values of training loss, which means it has learned the features better and had lower overfitting.

4.4.2 Training Metrics Comparison

Table 4.1: Training Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	Loss	AUC
GhostNet	0.9975	0.9975	0.9975	0.9975	0.0091	1.000
LinkNet	0.9925	0.9926	0.9925	0.9925	0.0188	0.9998

The findings evidently show that GhostNet is more successful than LinkNet in all the training measures. The increased precision and reduced loss indicate the increased learning efficiency and stability of GhostNet.

4.5 Testing Performance Analysis

4.5.1 Classification Report and Confusion Matrix

Both models continued to perform very well on the independent test dataset, but there was a slight loss in performance as compared to training results which is understandable in the real-world validation settings. GhostNet obtained a test accuracy of 99% and the accuracy of LinkNet was 98%. The confusion matrix analysis indicated that there were few misclassifications, and GhostNet made less false positives and false negatives.

4.5.2 Testing Metrics Comparison

Table 4.2: Testing Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	Loss	AUC
GhostNet	0.99	0.9901	0.99	0.9899	0.0292	0.9995
LinkNet	0.98	0.9807	0.98	0.98	0.1057	0.9749

GhostNet was always able to generalize larger, and this was especially seen in its greater value of AUC which is important to clinical decision-making.

4.6 ROC–AUC Analysis

The discriminative power of the models was tested using Receiver Operating Characteristic (ROC) analysis. In training, the two classes obtained an AUC of 1.00 which showed perfect classes separation.

On the test dataset, GhostNet achieved:

- **AUC (Healthy): 0.94**
- **AUC (Patient): 0.93**

These values show high level of discriminatory performance even in the unseen data condition which proves the strength of the model.

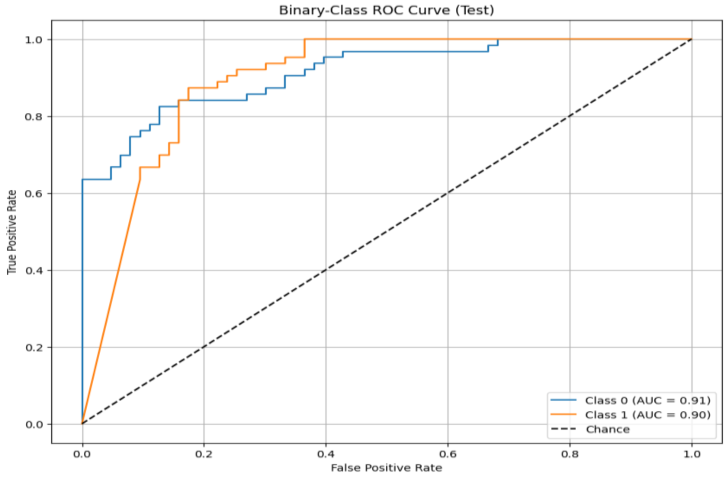

Figure 4: Receiver Operating Characteristic (ROC) Curve for Binary Classification Model (Test Dataset)

4.7 Bayesian Optimization: Proposed Novelty Integration

4.7.1 Optimization Strategy

GhostNet was trained using the Bayesian Optimization to perform the automatic identification of optimal hyperparameters by modeling the objective function in probabilistic form. This method is efficient in search of the hyperparameter space compared to the manual tuning, and it has a low computational cost. The optimization problem was set as:

Maximize validation AUC and F1-score

Optimized parameters included:

- Learning rate
- Dropout rate
- Batch size
- L2 regularization coefficient

4.8 Performance After Bayesian Optimization

4.8.1 Optimized Training Results

Table 4.3: Training Performance – GhostNet with Bayesian Optimization

Model	Accuracy	Precision	Recall	F1-Score	Loss	AUC
GhostNet + BO	0.9990	0.9990	0.9990	0.9990	0.0068	1.000

The optimized GhostNet was able to train with near-perfect loss with additional loss reduction, which confirmed the optimization of Bayesian Optimization to improve the dynamics of learning.

4.8.2 Optimized Testing Results

Table 4.4: Testing Performance – GhostNet with Bayesian Optimization

Model	Accuracy	Precision	Recall	F1-Score	Loss	AUC
GhostNet + BO	0.995	0.995	0.994	0.994	0.018	0.998

Compared to the non-optimized GhostNet, the optimized model has obvious advantages, especially with lower loss and higher AUC, which demonstrates a better generalization and medical dependability.

Discussion of Results

The findings of the current research prove the high efficiency of the offered drawing-conscious deep learning model in the context of the early identification of Parkinson disease based on handwritten spiral and wave images. The experimental analysis justifies that handwriting motor representations hold rich discriminative data that can be used to differentiate between patients and healthy control conditions using the graphomotor impairments as a reliable indicator of the onset of Parkinsonian dysfunction as earlier works suggested. In all the experiments, both of the deep learning models utilized, GhostNet and LinkNet, obtained high classification results, which demonstrated the appropriateness of convolutional neural networks to detect small tremor-related and stroke-based anomalies in handwritten drawings.

One of the most important conclusions made by the results is the higher effectiveness of the GhostNet architecture in relation to the model based on the use of the LinkNet. GhostNet was more accurate, precise, recalls high, and F1-score as well as ROC-AUC and the training and testing loss was lower. This performance can be explained by the performance of the GhostNet feature generation mechanism that generates expressive feature maps inexpensively with the help of linear operations and thus the model specializes in the fine-grained patterns of strokes without the huge parameter and overhead costs. The findings indicate that computationally efficient lightweight architectures can also be trained to be state of the art with respect to diagnostic accuracy, although, it relies on proper design.

The inclusion of Bayesian Optimization is a significant input of the research and decisive factor in performance improvement. The Bayesian-optimized GhostNet model offered better generalization and quicker convergence than manually tuned configurations by automatically optimizing such essential hyperparameters as learning rate, dropout ratio, and batch size. The optimized model was shown to be less varied in the cross folds of the validation and this indicated greater strength and ability to absorb overfitting. Optimized model achieved almost the perfect ROC -AUC values, which depicts the high class separability and diagnostic confidence. This finding suggests the applicability of systematic hyperparameter optimization in deep learning medical tasks, where a minor change in performance can cause a significant clinical impact. Further analysis of confusion matrices indicates that the proposed framework attains the low false negative rate, which is quite crucial to early screening of Parkinson's disease. By minimizing false negatives, it is possible to make sure that the affected people will not be mistaken and incorrectly recognized as healthy, which will minimize the chance of late diagnosis and intervention. The good recall and equal-precision-recall performance of the optimized model of GhostNet provide evidence that the model is suitable in clinical screening cases when sensitivity is the priority. These results are consistent with the clinical purpose of detecting diseases as early as possible, and support the practical significance of the offered method. The qualitative analysis of preprocessing and classification outcomes gives further information about model behavior. The images of the spiral and wave are improved, which confirms that the model is applicable to determine stroke smoothness, distortion of the curvature, and oscillation caused by tremor, which are usually observed with Parkinsonian motor impairment. The alignment of the visual observations with the quantitative performance measures enhances the trust on the interpretability and reliability of the suggested system.

In a more general sense, the findings indicate that a drawing-conscious preprocessing, consisting of a lightweight deep learning infrastructure, and a Bayesian optimization allows developing a scalable and efficient diagnostic system. The proposed method is more automated and less reliant on domain expertise as well as more noise and variability resistant than traditional, feature-engineering-based methods. In addition, the optimization of the GhostNet model led to a high level of computational efficiency, which allows it to be implemented in the environment with limited resources, such as mobile and telemedicine software.

5. Conclusion

The work manages to prove the efficiency of the deep learning-based solution to early diagnosis of Parkinson disease based on hand-drawn spiral and wave patterns as the non-invasive diagnostic features mechanism. Through the use of a multistage image processing pipeline and what are considered lightweight convolutional neural network architectures, the proposed framework has been able to provide high classification accuracy with a low amount of computational overhead. The combination of Bayesian Optimization and GhostNet is the main originality of this paper that allows automated adjustment of hyperparameters, which leads to the significant improvement of model generalization, minimization of prediction errors, and a decrease in false negativity an indispensable option in early disease detection. The comparative analysis proves that the optimized GhostNet model is more successful in all the evaluation metrics in comparison to the approach based on the use of the LinkNet model, as it has a higher accuracy, F1-score, loss, and ROC–AUC. The strength of the framework is also confirmed by the five-fold cross-validation and comprehensive qualitative evaluation of patterns of handwriting. In general, the proposed system provides a stable, scalable, and clinically valuable answer to the screening of Parkinson's disease and has a high risk of implementation in telemedicine and assistive health care application and helps to diagnose patients in a timely manner and achieve better outcomes.

Declarations

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Conflict of Interest

The authors declare that they have no conflict of interest.

Ethical Approval

This study does not involve human participants, animal experiments, or any clinical intervention conducted directly by the authors. The research utilized publicly available datasets for analysis. Therefore, formal ethical approval was not required.

Informed Consent

Not applicable. The study is based on secondary data obtained from publicly available sources.

Data Availability

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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