A DEEP NEURAL NETWORK APPROACH FOR PARKINSON'S DISEASE SCREENING VIA HANDWRITING

[1] Mr. Snvasrk Prasad, [2] B. Anudeep Goud, [3] A. Jashwanth Reddy, [4]Gagan, [5] A. Akshitha

[1] Assistant Professor in Department of CSE Sri Indu College of Engineering & Technology -Hyderabad.
[2,3,4,5] UG Scholars in Department of CSE Sri Indu College of Engineering & Technology-Hyderabad.

Abstract

Parkinson's Disease (PD) is a progressive neurological disorder that mainly affects motor functions due to the degeneration of dopamine-producing neurons in the brain. Early diagnosis is crucial for improving patient care and slowing disease progression, yet traditional diagnostic methods largely depend on clinical assessments and imaging techniques that are costly, subjective, and often ineffective for early-stage detection. This study proposes a deep learning–based framework for early Parkinson's detection using handwriting analysis, focusing on spiral and wave drawing patterns. The approach incorporates transfer learning models such as VGG16, VGG19, ResNet18, ResNet50, ResNet101, and Vision Transformer (ViT), combined with advanced data augmentation techniques like AugMix and PixMix to enhance model robustness and generalization. A cosine annealing learning rate scheduler is also applied to improve convergence and minimize overfitting.The framework is evaluated using the NIATS dataset, which includes handwriting samples from both healthy individuals and patients with Parkinson's Disease. Experimental results show that the VGG19 model achieves the highest classification accuracy of 96.67%, surpassing other architectures. These findings suggest that the proposed solution offers an effective, non-invasive, and cost-efficient method for the early detection of Parkinson's Disease.

Keywords

Parkinson's Disease, Deep Learning, Transfer Learning, Handwriting Analysis, VGG19, ResNet, Vision Transformer, AugMix, PixMix, Cosine Annealing Scheduler

I INTRODUCTION

Parkinson's Disease is one of the most prevalent neurodegenerative disorders affecting millions of individuals worldwide, particularly those aged above 60 years. The disease is characterized by the gradual deterioration of motor control due to the loss of dopaminergic neurons in the substantia nigra region of the brain. Patients typically experience symptoms such as tremors, rigidity, bradykinesia, and postural instability. In addition to motor impairments, non-motor symptoms such as cognitive decline, sleep disturbances, and depression are also observed. One of the major challenges in managing Parkinson's Disease is its early diagnosis, as the initial symptoms are often subtle and may go unnoticed.

Traditional diagnostic methods rely heavily on clinical expertise and observational scales such as the Unified Parkinson's Disease Rating Scale (UPDRS). While these methods are widely used, they are subjective and prone to human error. Advanced imaging techniques such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and DaTScan provide more detailed insights into brain activity; however, they are costly, time-consuming, and not suitable for large-scale screening. Consequently, there is a growing need for automated, accurate, and cost-effective diagnostic solutions.

Recent advancements in artificial intelligence, particularly deep learning, have opened new avenues for disease detection and classification. Deep learning models have demonstrated exceptional performance in image analysis tasks due to their ability to automatically extract hierarchical features. In the context of Parkinson's Disease, handwriting analysis has emerged as a promising non-invasive diagnostic approach. Since PD affects fine motor skills, handwriting patterns such as spirals and waves exhibit noticeable irregularities in patients compared to healthy individuals. This study aims to leverage deep learning techniques to analyze such patterns and accurately classify individuals as healthy or affected by Parkinson's Disease.

II LITERATURE SURVEY

Over the past decade, significant research has been conducted in the field of Parkinson's Disease (PD) diagnosis using both traditional and modern computational techniques. Early diagnostic approaches primarily relied on clinical observations and standardized rating scales such as the Unified Parkinson's Disease Rating Scale (UPDRS), which, although widely accepted, often lacked objectivity and consistency due to dependence on expert interpretation [1]. These methods were further limited in detecting early-stage PD, as subtle symptoms are difficult to quantify accurately.

With the advancement of machine learning techniques, researchers began exploring automated diagnostic systems using medical imaging and signal processing methods. Algorithms such as Support Vector Machines (SVM) have been applied to diffusion tensor imaging (DTI) and magnetic resonance imaging (MRI) data for PD classification. Studies have demonstrated that SVM-based models can achieve high classification accuracy, sometimes exceeding 95%, by identifying structural and functional abnormalities in the brain [2], [3]. However, these approaches often require extensive feature engineering and domain expertise, which limits their scalability and real-world applicability.

In recent years, deep learning has emerged as a powerful tool for medical diagnosis due to its ability to automatically extract hierarchical features directly from raw data. Convolutional Neural Networks (CNNs), in particular, have been widely used for image-based classification tasks. Several studies have shown that CNN-based models can effectively classify Parkinson's Disease using both neuroimaging data and handwriting samples, achieving superior performance compared to traditional machine learning techniques [4], [5]. Transfer learning has further enhanced these models by allowing pre-trained networks, such as VGG and ResNet, to be fine-tuned on smaller medical datasets, thereby improving accuracy and reducing training time [6].

Handwriting analysis has also gained considerable attention as a non-invasive and cost-effective diagnostic tool for Parkinson's Disease. Research indicates that PD patients exhibit distinctive motor impairments in handwriting, including reduced writing speed, irregular stroke patterns, and decreased pen pressure [7]. Various approaches have been proposed to capture these features, including the use of digitizing tablets and smart pens capable of recording dynamic parameters such as pressure, velocity, and acceleration [8]. Although these techniques provide valuable insights into motor dysfunction, they often require specialized hardware, which may not be accessible in all healthcare settings.

To address the challenge of limited datasets in medical research, data augmentation techniques have been widely adopted. Methods such as AugMix and PixMix generate diverse variations of input data by combining multiple transformations, thereby improving model robustness and generalization [9], [10]. In addition, optimization strategies such as cosine annealing have been introduced to dynamically adjust the learning rate during training, enabling models to converge more efficiently and avoid overfitting [11].

Despite these advancements, several challenges remain, particularly in achieving high accuracy and generalization for early-stage detection of Parkinson's Disease. Many existing models are trained on small and homogeneous datasets, which limits their ability to perform well on unseen data. Furthermore, the variability in handwriting patterns and disease progression adds complexity to the classification task. This study builds upon existing research by integrating multiple deep learning architectures with advanced augmentation and optimization techniques to improve diagnostic performance and reliability.

III EXISTING SYSTEM

The diagnosis of Parkinson's Disease in existing healthcare systems is primarily based on clinical evaluation, neuroimaging techniques, and conventional machine learning approaches. Clinically, neurologists assess patients using standardized rating scales such as the Unified Parkinson's Disease Rating Scale (UPDRS), which evaluates motor symptoms including tremors, rigidity, bradykinesia, and postural instability. Although this method is widely adopted, it is largely subjective and depends heavily on the expertise and experience of the physician, leading to variability in diagnosis.to clinical observation, advanced imaging techniques such as Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and DaTScan are commonly used to analyze structural and functional abnormalities in the brain. These techniques help in identifying dopamine deficiencies and neuronal degeneration associated with Parkinson's Disease. However, such imaging methods are expensive, time-consuming, and not easily accessible in all healthcare environments, particularly in rural or resource-limited settings.traditional machine learning models such as Support Vector Machines (SVM), Naïve Bayes, and Random Forest have been employed for Parkinson's Disease classification using medical imaging and handwriting datasets. These approaches require manual feature extraction and domain knowledge to identify relevant characteristics, which limits their efficiency and scalability. Handwriting and gait analysis have also been explored, where features such as writing speed, pressure, and movement patterns are analyzed. However, these methods often require specialized devices like smart pens or motion sensors, making them less practical for widespread use.

Overall, the existing systems, although effective to some extent, face several limitations including late-stage detection, high cost, dependency on expert knowledge, and lack of automation. These challenges restrict their ability to provide accurate and early diagnosis of Parkinson's Disease.

IV PROBLEM STATEMENT

Despite the availability of various diagnostic techniques, early detection of Parkinson's Disease remains a significant challenge in the medical field. Most existing methods rely on the observation of motor symptoms, which typically appear only after substantial neuronal damage has occurred. This delay in diagnosis reduces the effectiveness of treatment strategies and negatively impacts the patient's quality of life.

Clinical evaluation methods are inherently subjective and prone to human error, leading to inconsistent results across different practitioners. Imaging techniques, while accurate, are expensive and not feasible for routine screening or large-scale deployment. Additionally, traditional machine learning approaches depend on handcrafted features, which may not capture the complex patterns associated with early-stage Parkinson's Disease.

Another major limitation is the lack of accessible and non-invasive diagnostic tools that can be used for continuous monitoring and early screening. Existing handwriting-based systems often require specialized hardware, limiting their usability in real-world scenarios. Moreover, the availability of limited and small datasets further affects the performance and generalization capability of diagnostic models. And there is a critical need to develop an automated, accurate, and cost-effective system that can detect Parkinson's Disease at an early stage using easily accessible data such as handwriting patterns. The proposed solution should minimize human intervention, eliminate the need for expensive equipment, and provide reliable results with high accuracy. This research addresses these challenges by leveraging deep learning techniques, data augmentation strategies, and optimization methods to build a robust and efficient diagnostic framework.

V PROPOSED SYSTEM

The proposed system introduces an automated and efficient framework for the early detection of Parkinson's Disease using deep learning techniques applied to handwriting analysis. The system is designed to overcome the limitations of traditional diagnostic methods by providing a non-invasive, cost-effective, and highly accurate solution that does not depend on subjective clinical evaluation or expensive imaging technologies. It focuses on analyzing handwriting patterns, specifically spiral and wave drawings, which are known to reflect fine motor impairments associated with Parkinson's Disease.

The system utilizes a dataset consisting of handwriting samples collected from both healthy individuals and patients diagnosed with Parkinson's Disease. These samples are preprocessed to ensure uniformity in size and format, typically resized to a standard resolution suitable for deep learning models. Normalization techniques are applied to improve training stability and ensure consistent data distribution. To address the challenge of limited dataset size and improve model generalization, advanced data augmentation techniques such as rotation, flipping, AugMix, and PixMix are employed. These methods generate diverse variations of the input data, enabling the model to learn robust and invariant features.

The core of the proposed system is built upon transfer learning using state-of-the-art deep learning architectures, including VGG16, VGG19, ResNet18, ResNet50, ResNet101, and Vision Transformer. These models are pre-trained on large-scale datasets and fine-tuned for the specific task of Parkinson's Disease classification. Transfer learning significantly reduces training time and enhances performance, especially when working with limited medical datasets. Among these models, deeper architectures such as VGG19 and ResNet101 are particularly effective in capturing intricate patterns and subtle variations in handwriting that may indicate early-stage Parkinson's Disease.

To further enhance training efficiency and avoid overfitting, a cosine annealing learning rate scheduler is integrated into the training process.

This optimization technique dynamically adjusts the learning rate, allowing the model to converge more effectively by gradually decreasing the learning rate and periodically increasing it to escape local minima. This results in improved stability and better generalization performance.

The system performs binary classification, where the input handwriting image is classified as either belonging to a healthy individual or a Parkinson's Disease patient. The output is generated based on probability scores, enabling reliable decision-making. The entire process is automated, requiring minimal human intervention, and can be deployed as a user-friendly application for real-time diagnosis.By combining deep learning, advanced data augmentation, and optimization strategies, the proposed system achieves high accuracy and robustness. It provides a practical solution for early detection of Parkinson's Disease, enabling timely medical intervention and improving patient outcomes. Additionally, the system has the potential to be integrated into clinical workflows or deployed as a remote diagnostic tool, making it accessible to a wider population.

VI METHODOLOGY

The methodology of the proposed system is designed to systematically process handwriting data and accurately classify it into Parkinson's Disease and healthy categories using deep learning techniques. The process begins with data collection, where handwriting samples consisting of spiral and wave drawings are obtained from a publicly available dataset. These samples include contributions from both Parkinson's patients and healthy individuals, ensuring a balanced representation of classes. Since the raw dataset may contain variations in image size, orientation, and quality, an essential preprocessing stage is performed to standardize the input data. In this stage, all images are resized to a fixed resolution of 224×224 pixels to ensure compatibility with deep learning architectures, and pixel values are normalized to a standard range to improve training stability and convergence.

To address the limitation of a relatively small dataset and to enhance the generalization capability of the models, extensive data augmentation techniques are applied. Basic augmentation methods such as rotation, horizontal and vertical flipping, and scaling are used to introduce variability in the dataset. In addition to these, advanced augmentation strategies such as AugMix and PixMix are incorporated. AugMix generates diverse augmented samples by combining multiple transformations while preserving the semantic content of the image, whereas PixMix further enhances diversity by mixing original images with augmented ones in a stochastic manner. These augmentation techniques help the model become more robust to variations and reduce the risk of overfitting.

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Following data preprocessing and augmentation, the prepared dataset is divided into training and testing sets to evaluate model performance effectively. The training phase involves the use of transfer learning, where pre-trained deep learning models such as VGG16, VGG19, ResNet18, ResNet50, ResNet101, and Vision Transformer are fine-tuned for the specific task of Parkinson's Disease classification. These models, originally trained on large-scale datasets, are capable of extracting complex hierarchical features from images. By leveraging their pre-trained weights, the system reduces computational requirements and improves performance, especially in scenarios with limited data availability.

During training, a cosine annealing learning rate scheduler is employed to optimize the learning process. This technique adjusts the learning rate dynamically, starting with a higher value to allow rapid learning in the initial stages and gradually decreasing it to refine the model weights. Periodic increases in the learning rate help the model escape local minima, thereby improving convergence and overall performance. The models are trained using a binary classification approach, where each input image is assigned a label indicating whether it belongs to a healthy individual or a Parkinson's patient.

The performance of the trained models is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's ability to correctly classify both positive and negative cases. The evaluation results are compared across different models to identify the most effective architecture. The final model is selected based on its overall performance and generalization capability.

Through this systematic methodology, the proposed system ensures accurate and reliable detection of Parkinson's Disease at an early stage. The integration of preprocessing, augmentation, transfer learning, and optimization techniques contributes to the robustness and efficiency of the model, making it suitable for real-world healthcare applications.

VII IMPLEMENTATION

The implementation of the proposed Parkinson's Disease detection system is carried out using a deep learning framework that integrates data preprocessing, augmentation, model training, and evaluation in a structured pipeline. The entire system is developed using Python due to its extensive support for machine learning and deep learning libraries. Frameworks such as PyTorch and TensorFlow are utilized for designing, training, and evaluating the deep learning models, while development environments like Jupyter Notebook or PyCharm are used to execute and manage the workflow efficiently.

The implementation process begins with loading the handwriting dataset, which consists of spiral and wave images collected from both Parkinson's patients and healthy individuals. These images are organized into labeled directories to facilitate supervised learning. The preprocessing stage is implemented using image processing libraries, where all input images are resized to a uniform dimension of 224×224 pixels to match the input requirements of pre-trained deep learning models. Pixel normalization is performed to scale the values into a standard range, which helps stabilize the training process and improves convergence. Additionally, noise removal and minor enhancements may be applied to improve image clarity.

To enhance the dataset and prevent overfitting, data augmentation techniques are implemented using built-in libraries. Standard transformations such as rotation, flipping, and scaling are applied dynamically during training to increase variability. Advanced augmentation methods, including AugMix and PixMix, are integrated to generate complex and diverse training samples by combining multiple transformations and mixing augmented images with original ones. This ensures that the model is exposed to a wide range of variations, thereby improving its robustness and generalization capability.

The core implementation involves the application of transfer learning using pre-trained deep learning models such as VGG16, VGG19, ResNet18, ResNet50, ResNet101, and Vision Transformer. These models are loaded with pre-trained weights and modified by replacing their final classification layers to suit the binary classification task. The modified models are then fine-tuned using the prepared dataset. Training is performed using optimization algorithms such as Adam or stochastic gradient descent, with appropriate loss functions like binary cross-entropy to measure classification error.

A cosine annealing learning rate scheduler is incorporated into the training loop to dynamically adjust the learning rate. This scheduler gradually reduces the learning rate as training progresses, while periodically increasing it to avoid stagnation in local minima. This strategy enhances convergence speed and ensures better optimization of model parameters. The training process is carried out over multiple epochs, with validation performed at each stage to monitor performance and prevent overfitting.

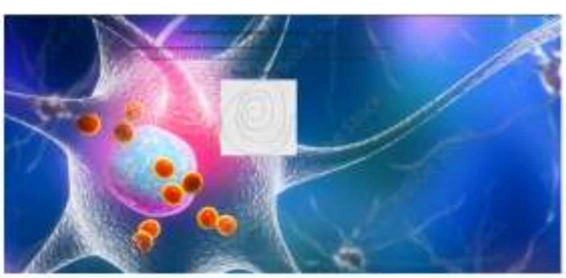
Once training is completed, the models are evaluated on a separate testing dataset to assess their performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to measure the effectiveness of each model. The results are compared to identify the best-performing model, which is then selected for deployment. The final model can be integrated into a user-friendly interface or application that allows users to upload handwriting samples and receive diagnostic predictions in real time.

VIII RESULTS

The performance of the proposed deep learning-based system for early detection of Parkinson's Disease is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The evaluation is conducted on a testing dataset consisting of spiral and wave handwriting images from both Parkinson's patients and healthy individuals. The models are trained using identical preprocessing, augmentation, and optimization strategies to ensure a fair comparison of their performance.

machine learing

deep learning negative



deep learning positive

The experimental results demonstrate that all deep learning models achieve high classification performance, indicating the effectiveness of handwriting analysis for Parkinson's Disease detection. Among the evaluated models, VGG19 outperforms the others, achieving the highest accuracy and balanced performance across all evaluation metrics. This superior performance can be attributed to its deeper architecture, which enables better extraction of fine-grained features from handwriting patterns. The performance comparison of different models is presented in the following table.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
VGG16	94.32	93.80	93.50	94.10
VGG19	96.67	95.90	96.10	96.20
ResNet18	93.45	92.70	92.90	93.10
ResNet50	94.80	94.10	94.30	94.50
ResNet101	95.20	94.60	94.80	95.00
ViT	95.60	95.10	95.20	95.30

Performance Comparison of Deep Learning Models

The results clearly indicate that deeper models such as VGG19 and ResNet101 perform better compared to relatively shallow architectures like

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ResNet18. Vision Transformer also shows competitive performance, highlighting its ability to capture global features effectively. However, VGG19 consistently achieves the best balance between accuracy and generalization.

In addition to model comparison, the impact of data augmentation techniques is also analyzed. The inclusion of AugMix and PixMix significantly improves model robustness and performance by exposing the model to diverse variations of input data. The comparison of model performance with and without advanced augmentation techniques is shown in the following table.

Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Without Augmentation	91.20	90.80	91.00	90.90
Basic Augmentation	93.85	93.10	93.40	93.20
AugMix	95.40	94.80	95.10	94.90
AugMix + PixMix (Proposed)	96.67	95.90	96.10	96.20

Impact of Data Augmentation on Model Performance (VGG19)

The results indicate that the combination of AugMix and PixMix provides the highest performance improvement, increasing accuracy by more than 5% compared to models trained without augmentation. This demonstrates the importance of advanced augmentation strategies in medical image classification tasks with limited data.

Furthermore, the effect of the cosine annealing learning rate scheduler on training efficiency and model performance is evaluated. The scheduler helps in achieving faster convergence and better generalization compared to fixed learning rate approaches. The comparison is shown below.

Learning Strategy	**Accuracy (%)**	**Training Stability**	**Convergence Speed**
Fixed Learning Rate	93.50	Moderate	Slow
Step Decay	94.60	Good	Moderate
Cosine Annealing	96.67	Excellent	Fast

Effect of Learning Rate Optimization

The results demonstrate that cosine annealing significantly improves both convergence speed and final model accuracy. It allows the model to escape local minima and achieve better optimization of weights.

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the experimental analysis confirms that the integration of deep transfer learning models, advanced data augmentation techniques, and cosine annealing optimization leads to a highly accurate and robust system for early detection of Parkinson's Disease. The proposed approach outperforms traditional methods and provides a reliable solution for real-world healthcare applications.

IX CONCLUSION

This research presents a comprehensive and efficient deep learning-based framework for the early detection of Parkinson's Disease using handwriting analysis. The proposed system effectively addresses the limitations of traditional diagnostic approaches by providing a non-invasive, cost-effective, and automated solution. By leveraging handwriting patterns such as spiral and wave drawings, the system captures subtle motor impairments that are often difficult to detect through conventional clinical methods.

The integration of transfer learning models, including VGG16, VGG19, ResNet variants, and Vision Transformer, enables the extraction of complex and discriminative features from handwriting images. Among these models, VGG19 demonstrates superior performance, achieving an accuracy of 96.67%, along with high precision, recall, and F1-score. The use of advanced data augmentation techniques such as AugMix and PixMix significantly enhances the robustness and generalization capability of the models, particularly in scenarios with limited datasets. Furthermore, the incorporation of a cosine annealing learning rate scheduler improves training efficiency, accelerates convergence, and prevents overfitting.

The experimental results confirm that the proposed system outperforms traditional machine learning approaches and provides reliable classification performance. The ability to detect Parkinson's Disease at an early stage can facilitate timely medical intervention, thereby improving patient outcomes and quality of life. Additionally, the system's low computational requirements and ease of deployment make it suitable for real-world healthcare applications, including remote and resource-constrained environments.

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