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DETECTION OF PARKINSON'S DISEASE FROM RETINAL FUNDUS IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Parkinson's disease (PD), a progressive neurological disorder that impairs quality of life and results in motor issues and cognitive decline, affects millions of people globally. Early diagnosis is essential for improving treatment outcomes, but conventional diagnostic techniques like MRIs, PET scans, and clinical evaluations are usually pricy, invasive, and unavailable, particularly in resource-constrained environments. This study aims to develop an automated, non-invasive diagnostic method for early PD detection using convolutional neural networks (CNN) and retinal fundus images. The publicly available Kaggle retinal fundus image dataset used in this study includes both healthy and age-related Macular Degeneration (AMD) images. To replicate PD-related retinal features, AMD images were reclassified as PD-like. Contrast Limited Adaptive Histogram Equalization contrast enhancement, optic disc detection, and blood vessel segmentation were all part of the preprocessing. The images were resized, normalized, and then processed using a custom CNN model that included multiple convolutional layers, batch normalization, max pooling, and dropout layers. The model achieved an impressive 99.1% F1-Score, 99.0% precision, 99.3% sensitivity, and 99.1% accuracy. These results demonstrate that retinal imaging is a practical, non-invasive PD screening technique. Notwithstanding the positive results, more research utilizing clinical-scale data and actual PD patient datasets is necessary to confirm the model's generalisability and applicability in healthcare settings.

Keywords: Biomedical image analysis, Clinical decision support, Convolutional neural networks, Parkinson's disease, Retinal fundus images.

1. Introduction

A progressive neurodegenerative disease affecting movement, PD causes symptoms including tremors, bradykinesia, and stiffness [1, 2]. Though difficult because of subtle early symptoms, early diagnosis is essential [3-6]. Expensive and needing specialized equipment, traditional diagnostic techniques, including MRI, PET scans, and clinical tests like the UPDRS, limit access [7-10].

Retinal imaging has lately become a promising non-invasive diagnostic tool for neurodegenerative diseases like PD [11]. Being an extension of the central nervous system, the retina exhibits structural and vascular changes that could be early signs of PD [6, 12]. Retinal abnormalities, including changes in blood vessel shape and optic disc features, have been highlighted in several studies as possible biomarkers for early-stage PD [13-16]. Deep learning and machine learning applied for PD detection using retinal fundus images have, however, faced constraints, including small datasets, lack of external validation, and inadequate investigation of alternative image sources.

This work presents a CNN-based approach for retinal fundus image classification to identify PD at an early stage. The main novelty of this work is the reclassification of AMD images as PD candidates, thus augmenting the dataset and enhancing the generalization of the model. By leveraging a bigger and more varied dataset, this work intends to improve the accuracy and dependability of PD diagnosis using retinal images, thus filling the void in present research [17]. Moreover, by using several image sources, this method aims to overcome the constraints of earlier research concentrated just on homogeneous or small datasets.

Reclassifying AMD images for PD detection does, however, create possible biases that need careful thought. As AMD and PD are different diseases, this reclassification may not fairly represent actual diagnostic categories. The performance of the model could be artificially raised by applying AMD-specific traits instead of those applicable everywhere to PD. Applied to larger and more varied populations devoid of AMD images, this technique also runs the danger of lowering clinical validity. Notwithstanding these difficulties, this work provides the foundation for a stronger and more applicable retinal imaging-based early PD detection technique development.

This study is motivated by the growing need for low-cost, non-invasive diagnostic tools for PD that can be generally used, particularly in resource-limited environments. Though several machine learning and deep learning models have been investigated, the limited scope of datasets and validation has prevented many from reaching satisfactory generalization. This work intends to solve these problems by applying a CNN architecture with improved diagnosis accuracy and more varied dataset incorporation. We think that early PD detection will be much improved by combining retinal imaging with deep learning, thereby improving patient outcomes.

The paper is laid out as follows: Methodology defines the techniques of segmentation, data collection, and preprocessing. Architectural Deep Learning Model shows layers and the CNN model. Model Evaluation and Training: Discussing the outcomes, training setups, and metrics. Outcomes presenting performance measures like recall and accuracy; Related works, reviewing prior field research studies; discussions; analysis of the findings and limitations; and

concluding thoughts and future directions: We are suggesting possible future upgrades for PD detection.

2. Method

2.1. Proposed architectural design system

This work proposes a deep learning framework for CNN-based PD detection from retinal fundus images. Retinal images are supposed to extract pertinent features, classified into PD and healthy categories, and finally offer a quick, non-invasive diagnostic tool for early-stage PD. Figure 1 illustrates the general CNN architecture flow used for PD detection, guiding the system architecture.

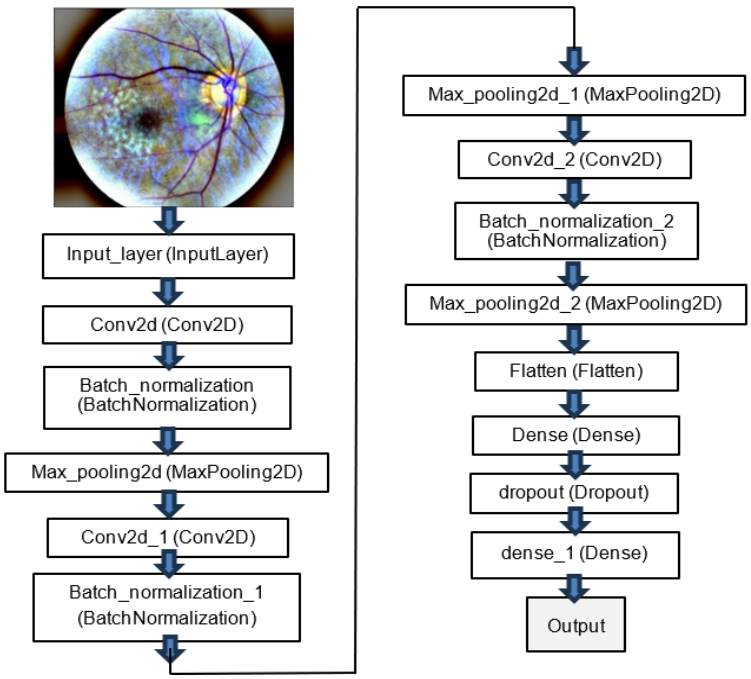

Fig. 1. Convolutional neural network architecture for detecting Parkinson disease from retinal images.

2.2. Dataset description

The publicly available Kaggle Retinal Fundus Images dataset was used [18], containing:

- AMD dry.
- AMD wet.
- Typical Fundus, or Healthy Control.

Though this dataset does not specifically mention a class for PD, recent studies have revealed that retinal vascular changes seen in AMD and AD mirror those found in PD [19-21]. The AMD dry and wet groups were reclassified as PD candidates to mimic retinal anomalies linked with PD given the common co-

occurrence of AD and PD and their overlapping retinal biomarkers. The normal fundus category stayed in the healthy control group.

Using this reclassification, we added vascular and structural retinal characteristics usually found in neurodegenerative disorders, therefore improving the model's capacity to identify early-stage PD. This strategy offers a new way to find possible PD-related patterns by increasing dataset diversity and helping to compensate for the absence of PD-specific fundus images.

Three subsets comprised the dataset:

- Training Set: Designed to equip the model. The training set comprises sixty percent of the model.
- Validation Set (20%): Designed to prevent overfitting and fine-tune hyperparameters.
- Test Set (20%): Performance of the last model assessed.

Class weights were applied during model training to balance PD and healthy classes, preventing bias toward the majority class. Steps Workflow Diagram as shown in Fig. 2.

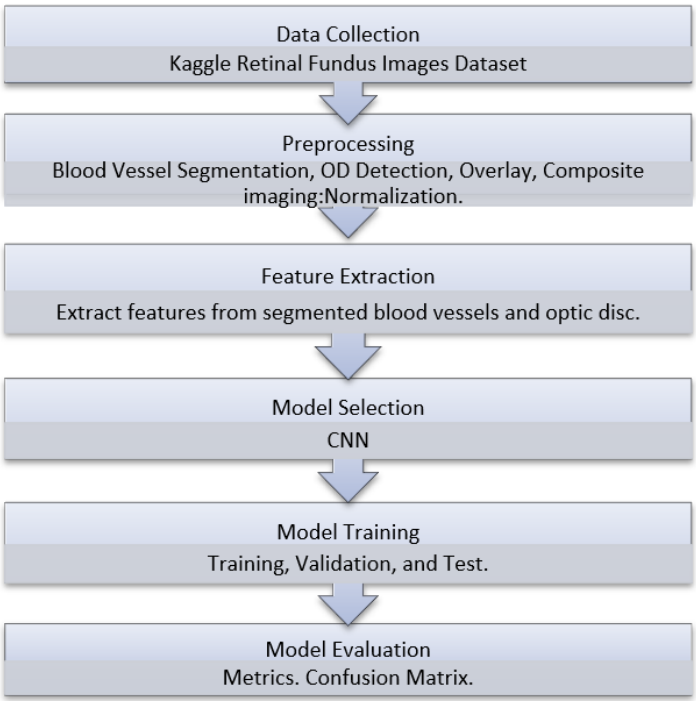

Fig. 2. Steps workflow diagram.

2.3. Preprocessing images and feature extraction

To ensure that the model effectively identifies key features in the retinal fundus images, several preprocessing and feature extraction techniques were employed. These steps are critical for enhancing the model's ability to detect subtle changes in the retina that may be indicative of PD.

- Blood Vessel Segmentation: Applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance vascular structure.
- Optic Disc Segmentation: Used thresholding techniques to isolate and analyse the optic disc.
- Normalization: Resized image to 224 × 224 pixels and normalized pixel values between [0.1] to improve model convergence.

By applying these preprocessing and feature extraction techniques, we improved the visibility of crucial retinal structures like the blood vessels and optic disc. These enhancements are vital for the CNN to learn meaningful patterns and features that could indicate the presence of PD. Figure 3 shows the preprocessing sequence. Figure 4 shows before model training, final reprocessed retinal fundus image. The image normalization formula is presented in Eq. (1).

$$X' = \frac{X - Xmin}{Xmax - Xmin} \tag{1}$$

where, X is the original value you want to normalize, Xmin is the smallest value in the dataset, Xmax is the largest value in the dataset, and X' is the new normalized value.

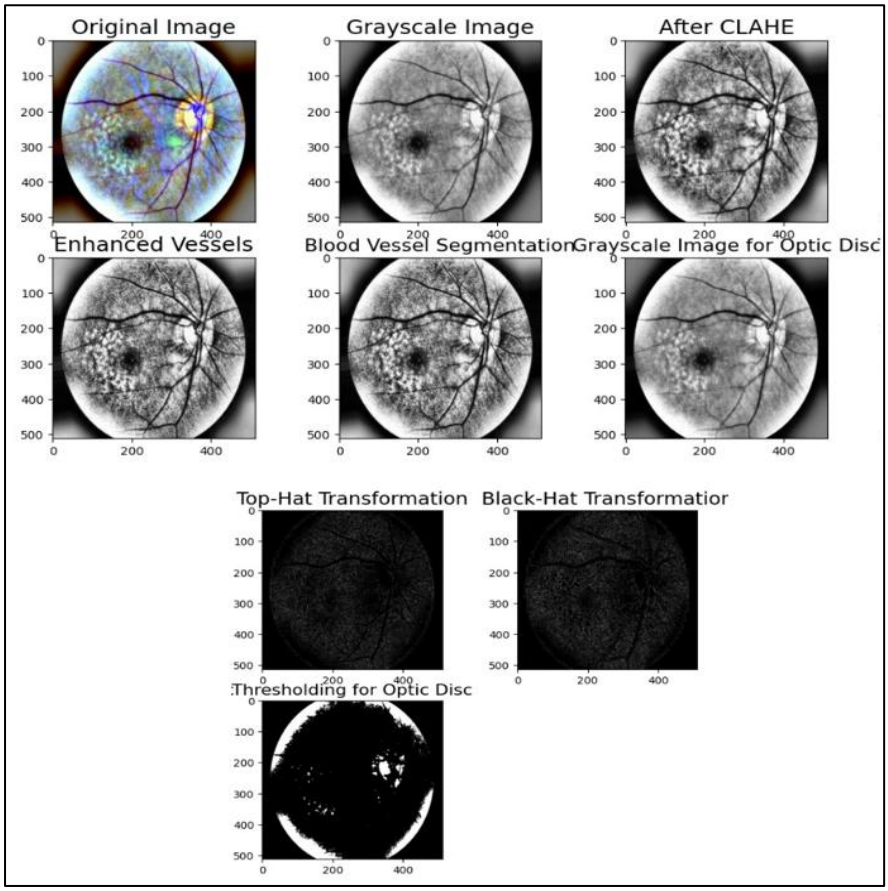

Fig. 3. Original image, CLAHE enhancement, top-hat, black-hat, blood vessel and optic disc segmentation: step-by-step preprocessing.

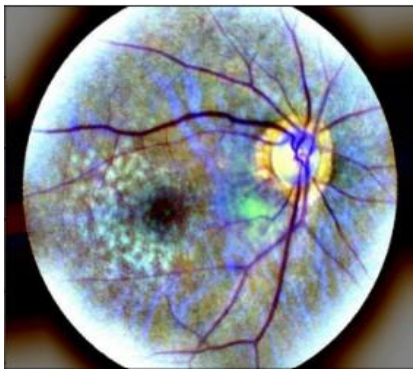

Fig. 4. Before model training, final reprocessed retinal fundus image.

2.4. Architectural deep learning model

CNN model architecture conforms to a conventional design for image classification problems Chollet [22]. Figure 5 displays the CNN's schematic from which PD is detected from retinal fundus images. The model comprises the following levels.

- **Input Layer**: Processes 224 × 224 × 3 images, integrating segmented features.

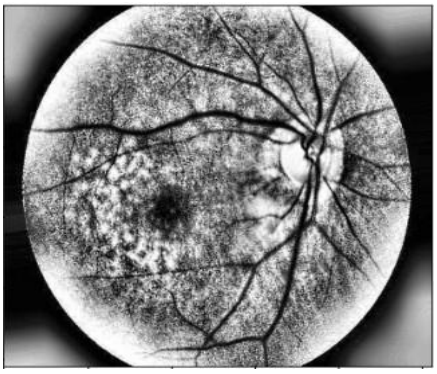

Fig. 5. Input to CNN mode: combined features (normalized).

- **Convolutional Layers.**
  - **Block** 1: 64 filters (3×3 kernel) → Max Pooling → Batch Normalization.
  - **Block** 2: 128 filters → Max Pooling → Batch Normalization.
  - Block 3: 256 filters → Max Pooling → Batch Normalization.
- **2D Convolution Operation:** A 2D convolution is represented by Eq. (2), whereby an image I(x, y) is convolved with a kernel k(m, n). Using the kernel as it moves across the image, this operation calculates a weighted sum of pixel values.

$$(I * k)(x, y) = \sum_m \sum_n I(x - m, 2 - n)k(m, n) \quad (2)$$

- **Fully Connected Layers**: Flatten → Dense (128 neurons) → Dropout (50%) → Output (Sigmoid activation for binary classification).

- **Training:** Adam optimizer, binary cross-entropy loss, batch size 32, 100 epochs, and early stopping applied (Sorathiya et al. [23]).
- **Binary Cross-Entropy Loss:** The Binary Cross-Entropy Loss function is given by Eq. (3).

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (3)$$

where, L: Loss value, N: Number of samples, Yi: Actual label (0 or 1), $y\,\hat{\imath}$: Predicted probability, Log: Natural logarithm, and $\sum$: Summation across all samples.

2.5. Implementation and results

Accuracy and loss visualizers show the model's outcomes. With the test accuracy reflecting the last assessment of the model's capacity to generalize unseen data, the training and validation accuracy displayed in Fig. 6 show the model's performance over time.

This paper presents a CNN built to classify retinal fundus images using important changes to improve performance. Unlike traditional classification models, this one combines blood vessel and optic disc segmentation as preprocessing techniques. The segmented features are merged into a three-channel input image, which offers more structural information to the model. Comprising three convolutional layers, the CNN design guarantees improved feature extraction, and less internal covariate shifts by means of batch normalization and max pooling following each layer.

A dropout layer with a 0.5 rate was added to help to prevent overfitting. Facilitating binary classification, the dataset was classified into "Parkinson" and "Healthy". To enhance model convergence, image data normalization, dividing pixel values by 255 was applied. Performance was evaluated using accuracy and loss visualizations; the training process included a validation split to track overfitting. Ultimately, test accuracy measures helped to assess the model's performance and offer insights into its actual use.

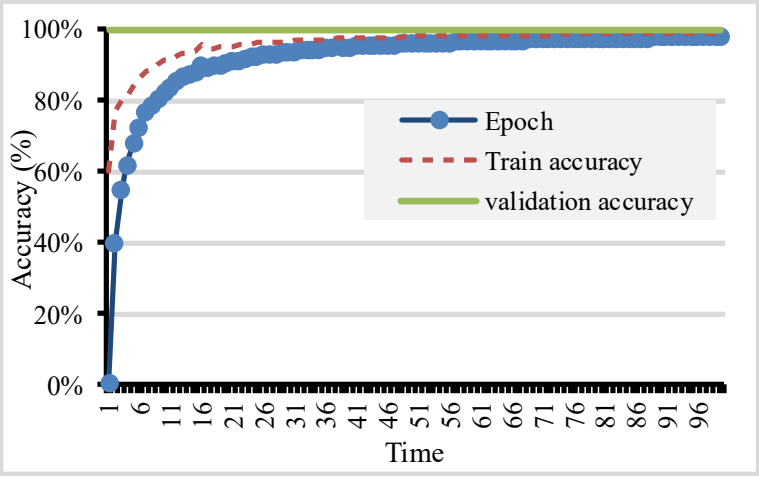

Fig. 6. Initially displaying the training and validation accuracy.

3. Results and Discussion

Using retinal fundus images, the deep learning model showed high performance in detecting PD. With an overall accuracy of 99.1%, the evaluation metrics show strong classification ability, implying that the model consistently distinguishes between PD and healthy cases, as in Table 1.

Table 1. Model performance metrics for CNN.

Metric	Value
Accuracy	99.1%
Precision	99.0%
Recall	*99.3%*
F1-Score	99.1%

Accuracy Calculation:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (4)$$

where, TP is correctly forecasted positive cases, with PD correctly predicted, TN is correctly forecasted negative cases (Healthy correctly predicted), FP, is incorrectly forecasted positives (false alarms) (Healthy incorrectly predicted as PD), FN is missed detections, wrongly predicted negatives, with PD incorrectly predicted as Healthy.

F1-Score calculation:

$$F1 = 2 * (Precision * Recall)/(Precision + Recall) \quad (5)$$

where: $Precision = TP/(TP + FP)$, $Recall = TP/(TP + FN)$.

3.1. Confusion matrix

The confusion matrix in Fig. 7 offers a more detailed perspective of the classification results, so supporting the strong performance of the model:

- 504 healthy images were correctly classified.
- 381 PD images were correctly classified.
- 3 false positives and 5 false negatives

The model showed remarkable sensitivity in finding true PD cases with a high recall value of 99.3%, so it is especially helpful for early detection. Clinically, reducing false negatives is essential since misdiagnosing PD patients as healthy could postpone required interventions.

All things considered, these results underline the possibility of deep learning models to offer an exact, quick, and non-invasive approach for early PD detection via retinal fundus imaging. To verify the model's strength in actual clinical environments, though, more validation on larger and more varied datasets is absolutely required.

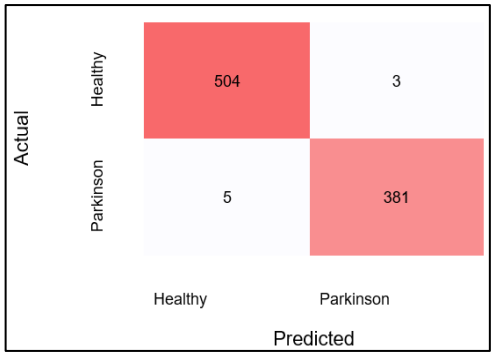

Fig. 7. Confusion matrix outcomes for the categories of PD and healthy.

3.2. Comparison with previous works

Recent research on early PD detection using deep learning and retinal fundus images reveals encouraging outcomes. There are still some issues and restrictions, though.

- Diaz et al. [24] discovered a link between PD and changes in retinal vasculature, such as blood vessel narrowing. Although machine learning models found these trends, the research ignored other possible retinal biomarkers, including optic disc and macular alterations. Furthermore, restricted outside validation calls into question generalizability.
- Ahn et al. [25] achieving above 80% sensitivity in detecting neurological dysfunction in PD using applied clinical scales such as Hoehn & Yahr (H-Y) and UPDRS-III. Relying on a small number of clinical scales, though, might not completely reflect the varied progression of PD. Improving diagnostic accuracy calls for a larger patient population.
- Arslan et al. [26] improved model interpretability by means of CAM, showing good internal validation (80% sensitivity). External validation, on the other hand, fell to 70.73%, so stressing difficulties in generalizing outcomes across several datasets. The drop in performance emphasizes the challenge of guaranteeing model robustness in diverse clinical environments.
- Pitchumani Angayarkanni and Kolengadan [19] used vessel tortuosity and intensity as main features; attained a high accuracy of 97.17%. However, questions about scalability and real-world applicability arise from depending on a small dataset and no independent validation. Small sample sizes often miss patient population diversity, so limiting generalizability.
- Tran et al. [27] showed moderate diagnostic ability with an AUC of 0.77. Though, especially in early stages, the model's low accuracy (68%) indicates it may struggle to differentiate PD from other neurological disorders. This underlines the difficulty of creating consistent early detection systems.

Table 2 contrasts the performance of the model of this work with earlier studies using retinal fundus images using the same techniques for PD detection.

While earlier studies, such as Pitchumani Angayarkanni and Kolengadan [19], attained high accuracy (97.17%), they were limited by an imbalanced dataset and a lack of validation. Diaz et al. [24] also showed encouraging results, but their

method lacked generalizability and did not use deep learning. Conversely, this work's model outperformed previous methods in terms of both detection and generalization since it attained a 99.1% accuracy and 99.3% recall.

Table 2. Related works and comparison.

Authorship	Dataset	Methodology	Observations	Accuracy (%)	Recall (%)	Limitation
Diaz et al. [24]. 2020	UKB & UF-UKB	Vascular feature-based machine learning	Focused on vascular changes	85.2	82.5	No deep learning, little generalizability
Ahn et al. [25]. 2023	Independent hospital data sets 615 participants	A retinal image-based machine learning. predicted PD severity	Used the Hoehn & Yahr scale for severity prediction	70.45	80.0	Small sample size, no external validation
Arsalan et al. [26]. 2023	Private dataset	Deep learning classification model used on a private retinal image dataset	Lower external validation performance	70.7	80.0	Private dataset increases overfitting risk; no public validation limits
Pitchumani Angayarkanni and Kolengadan [19]. 2024	Kaggle retinal-fundus-images (reclassified), DRIVE	Applied CNNs to vessel tortuosity and intensity taken from Kaggle fundus images	Used retinal features (tortuosity & vessel intensity)	97.2	95.2	Dataset imbalance and restricted clinical context; more real-world testing required
Tran et al. [27]. 2024	UK Biobank	Non-invasive PD detection using deep learning on UK Biobank fundus photographs	Focused on non-invasive PD screening using deep learning	68.0	77.0	Moderate accuracy; low model understanding
This Study	Kaggle retinal-fundus-images (reclassified)	Optic disc analysis + CNN + CLAHE-enhanced vessel segmentation	Integrates optic disc and blood vessel features	99.1	99.3	Depends on Kaggle data; requires outside confirmation

4. Discussion and Analysis

Although the findings of this study show encouraging results, some issues should be addressed for future work.

- Variations in the dataset: The model was trained using a reclassified Kaggle dataset devoid of real PD images. Limiting generalizability. Future research should include a more varied collection of retinal images, including those labelled for PD, and validate the model across several datasets to assess its robustness in many clinical environments.
- Real-World Applicability: Using a single dataset begs questions about the model's capacity to manage real-world variability, even with the outstanding

outcomes. Demonstrating the clinical relevance of the model depends on external validation using datasets from many populations, including those with varied stages of PD.

- Additional Review using Statistical Validation: Statistical tests, including t-tests or ANOVA, could be used to ascertain whether the performance variations among models are statistically significant, thereby improving the assessment of the performance of the model. This would help one to have a better awareness of the possibilities and constraints of the model.

5. Conclusions

With retinal fundus images, this work shows the potential of deep learning, especially CNNs, for early detection of Parkinson's disease (PD), achieving an accuracy of 99.1%. The model emphasises retinal biomarkers as main PD indicators, including changes in blood vessels and the optic disc. These results imply that retinal imaging could be a non-invasive and reasonably priced screening tool for early Parkinson's disease development.

Reclassifying AMD images and a small dataset size, however, may compromise generalisability and clinical applicability. Further validation and wider application depend on bigger, more varied datasets. Particularly in environments with limited resources, this method could allow early PD diagnosis, thereby improving patient outcomes. Future projects should focus on making use of actual PD fundus pictures, diversity of expanding datasets, applying explainable artificial intelligence for clinical openness, and working with neurologists to verify biomarkers.

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Abbreviations

AD	Alzheimer's Disease
AMD	Age-related Macular Degeneration
CAM	Class Activation Maps
CLAHE	Contrast Limited Adaptive Histogram Equalization
CNNs	convolutional neural networks
DRIVE	Digital Retinal Images for Vessel Extraction
PD	Parkinson's Disease
RF	Random Forest
SVM	Support Vector Machine
UF	University of Florida
UKB	UK Biobank
UPDRS	Unified Parkinson's Disease Rating Scale

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