Enhancing Parkinson's Disease Detection with a GAN-CNN Hybrid Dual-Stream Model

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Abstract. Parkinson's disease is a chronic and progressive neurodegenerative disorder that affects movement. The clinical diagnosis for Parkinson's disease is made through neurological examination and imaging techniques like MRI and a DaT scan. So, the MRI Scan is used in this approach. Traditional diagnostic approaches using MRI data often encounter challenges, including data scarcity, low image quality, and model overfitting. To overcome challenges, this approach uses GAN and CNN. GAN handles generating synthetic images and integrates with real images. The combined data is used as input for the CNN classifier for training, this model is named the GAN-CNN hybrid dual stream model. This model is capable of detecting the early stage of Parkinson's and is more suitable than the other existing models, such as MobileNet, YOLOv7, and 1D-CNN. By leveraging synthetic data generation and deep learning classification, this model demonstrates improved performance on Parkinson's disease detection and performs well compared to existing systems, and the application of this model extends to real-world diagnostics, potentially enabling early and accurate detection of Parkinson's disease, thereby improving patient outcomes and treatment strategies.

Keywords: Parkinson's Disease, Neurodegenerative Disorder, Movement Disorder, Clinical Diagnosis, MRI Scan, DaT Scans, CNN-GAN Hybrid Model, Early Stage Detection, Yolo, Ensemble Net, Swin Transformer, Accuracy (85%, 98%), F1 Scor, GAN-CNN Hybrid Dual Stream.

1 Introduction

Parkinson's disease (PD) is a progressive, long-term, neurodegenerative disorder characterized by motor dysfunction due to the loss of dopaminergic neurons in the brain [1],[2]. The study aims at developing a GAN- CNN hybrid dual-stream model to enhance early detection of Parkinson disease from medical imaging data [3]. A hybrid approach leverage GANs to generate high-quality synthetic images and integrate these with real images to carry out training of a Convolutional Neural Network (CNN) which can improve the classification accuracy and robustness [4],[5]. In the present era, early detection of Parkinson's disease is very important due to its increasing incidence in the aging population and lack of effective biomarkers for early diagnosis [6,7]. In addition to that, a precise early diagnosis has the potential to significantly improve patient results with timely management and personalized treatment strategy [8,9,10]. This study demonstrates applicability to clinical diagnostics, will aid hospital decisions, is convenient for use in low-resource areas and could potentially be implemented within telemedicine platforms to extend remote evaluation. Furthermore, information obtained through this model may provide benefits for the general neurodegenerative research [11],[12],[13],[14].

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Diagnosis of Parkinson's disease: Most methods to date based on EEG, MRI, or imaging modalities. For instance, Siuly et al. proposed an architecture for the fusion of Wavelet Scattering Transform (WST) and AlexNet CNN for EEG classification [1]. Chatterjee and Bansal also developed a multimodal fusion technique that combined structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) data for enhanced diagnostic sensitivity [2]. Another system by Chen et al. introduced CTFF-Net, a CNN-Transformer based interleaved encoder deep learning network for segmentation of gray matter nucleiSeg2 which achieved accuracy up to 89% [3]. In addition, Tassew et al. a software project for PDDS integrates YOLO for region of interest detection and UNET-based models for segmentation (4). While they offer valuable improvements, these methods are limited in their reliance on high quality data, computational inefficiency and poor generalization to other datasets [5], [6]. Additionally, many may be specific to a single modality and limit their reach in different medical scenarios [7].

The GAN-CNN hybrid model offers a solution to circumvent these limitations by utilising synthetic data generation, limiting the reliance on large volumes of quality data and diversifying the training population [15]. When mixing GAN generated imaging and real data, the classification by CNN is more stable and accurate [6], [7]. Compared with existing methods, which are based on one modality or generalize different imaging modalities, our model has the ability of coping with poor medical image quality and keeping a high classification accuracy [4]. The model learns from a broad range of features and enhances its generalization / reliability by utilizing two streams (synthetic data, real-world data) [5], [6]. And notably, as stated in the abstract, it outperforms even state of the art models showing how well such a system can operate in actual diagnostic situations [7]. This is especially imperative in the context of early detection where early and precise diagnosis can dramatically impact upon treatment outcome as well as patient quality of life [8].

There are several advantages of the hybrid dual-stream GAN-CNN framework compared to existing systems. It improves generalization as it exploits the GANs to generate diverse synthetic data, preventing overfitting and increasing robustness [1], [2]. Second, by augmenting synthetic images with real ones during the training of the CNN [3,4], it greatly enhances the classification accuracy. The third point is that, the dual-stream structure in the model allows for concurrent processing of real and synthetical data and thus facilitates feature extraction [5]. The fourth advantage is that the model architecture of our approach requires significantly less computational resources, compared to the Transformer-based systems and can thus be implemented effectively even in clinically resource-limited settings [6]. The model's robustness to noise but also its performance on images from a variety of datasets name it such an attractive candidate which might be used in practice, for example, diagnosis in resource-restricted areas, integration into telemedicine initiatives as well as researches for the other neurodegenerative diseases [7],[8].

2 Related Work

Siuly et al. described an alternative approach using EEG for PDD on 2024, in Computers in Biology and Medicine. It concatenates the WST to represent the EEG time-series in time-frequency and a Convolutional Neural Network (CNN) built on AlexNet architecture for classification. This framework can capture the subtle details in EEG signals very well, and hence also the complex patterns associated with PD. It also indicates critical brain regions for the identification of PD. However, the performance of the model largely depends on the availability of good quality EEG data and model's reliance on some EEG channels such as AF4, AFz minds would limit its generalization ability, [1].

This method was also applied further in 2024 by Indranath Chatterjee and Videsha Bansal to improve diagnosis of PD using the sMRI and rs-fMRI data (independent work as well, Experimental Gerontology) [24]. The approach proposed contains i) Segmentation of the imaging data into localized regions, ii) Extraction of features iii) Representation learning using our CNN iv) Dimensionality reduction using PCA and v) A FFNN for Classification. The Diagnosis Is More Accurate and the Major PD-Related Brain Regions Are Easy to Identify by Integrating sMRI and rs-fMRI Data Nevertheless, the model provides classifications that are only 75% accurate thereof, which maybe not considered very high for some clinicians and could limit its wider applicability due to further reliance on both sMRI and rs-fMRI features [6].

In 2024, Hongyi Chen et al., presented their study for brain MRI with focus on segmenting PD-related deep gray matter nuclei using CTFF-Net, a deep network designed to perform automated segmentation. The network adopts an interleaved encoder consisting of CNN-Transformer and feature fusion module, and a symmetrical boundary attention module structure in the decoder to enhance segmentation accuracy. Problems such as appearance changes, poor tissue contrasts, and small size of deep gray matter nuclei are addressed with this approach. The deep architecture of this method can result in the higher computational expense even though it has strong capacity for accurate segmentation and cross-dataset generalizability over multi-center clinical, public data [2].

A paper in Biomedical Signal Processing and Control in 2023 by Tewodros Megabiaw Tassew et al. The final work, Parkinson's Disease Diagnosis Software (PDDS) was able to detect and segment deep brain regions from MRI (and DaTScan) images automatically based on images, using a deep learning approach. The software uses YOLO for object and region of interest (ROI) detection, as well as an ensemble of UNETs for segmentation. The personalized U-Net model has slightly below the segmentation performance while achieving high mean Average Precision (mAP) values and mean IOU intersection of MRI and DaTScan images, which would limit scalability by human labeling region of interest [7].

Nikita Aggarwal et al. demonstrated a multiclass classification in SWEDD scans belonging to PD and non-PD classes using 1-D CNN classifier with data augmentation method in their Biomedical Signal Processing and Control paper [26], which was an extended version of the work presented in REST. The paper addresses class imbalance issues and provides feature-wise data analysis in depth. The 1-D CNN model exhibits satisfactory performance in all classes, but the paper [8] does not explicitly mention the vulnerabilities of this method.

In 2025, in a paper published under Biomedical Signal Processing and Control Esra Yüzgeç and Fatih Özyurt started working to propose using Vision Transformer (ViT) models for wave, spiral images written by hand for PD classification. The proposed approach in our study combined the ViT models with ElasticNet for feature selection and other machine learning classifiers to perform better and faster than conventional deep learning classifiers. But the study authors do not compare this method to others state-of-the-art in the literature [5].

Nour El Houda BoulkrinatEt Al. tested the use of pre-trained CNN models MobileNet, ResNet50, AlexNet, VGG19 and InceptionV3— to predict PD based on MRIs in a study conducted by Procedia Computer Science in 2024. This method exploits data preprocessing operations for better image quality, and compares several models on the NTUA dataset. While it outscores on related work, the recall, precision and F1 values obtained were not satisfying as well as the high computational cost of BCNN model [9].

In 2023, Santhosh Kumar B. et al., published a Multimedia Tools and Applications paper based on OAssis-DL for PD classification using MRI images For feature extraction, the model employs frost filtering, local optimal oriented descriptor (LOOP) and discrete wavelet transform (DWletT) along with hunter-prey optimization method for classification. While the methodology effectively merges these modalities for feature extraction, no limitations of this proposed methodology were explicitly listed in [10].

Nada R. Yousif et al., J Ambient Intell Human Comput, 2023 Generic-templated framework for PD diagnosis from handwritten images and/or voice signals. The study uses pre-trained CNNs of handwritten images as well as machine-learning algorithms for voice signals, introducing an innovative voice segmentation algorithm. These results are admittedly better than many other state-of-the-art techniques, but have the cost of high learning time and processing [11].

Erik Dzotsenidze & al, 2022 In an IFAC Papers on Line study, the authors proposed in generative adversarial networks (GANs) for generating digital drawing tests from PD patients and healthy controls to solve the issue of a data shortage in computer-aided diagnosis [38]. The research presented the results of traditional data augmentation techniques on PD classification with CNNs across four different GAN architectures. While images from GAN were much better than the classical augmentation methods in any case, the small set of labelled data makes deep learning implementation on clinical imaging quite challenging [12].

Hajer Khachnaoui et al., IEEE Access in 2023 applied CNNs to diagnose PD using SPECT DATSCAN images, which was the main focus of this study. The research employs pre-trained models EfficientNet-B0 and MobileNet-V2 and a customized CNN architecture, which they fine-tune to diagnose PD [4].

In Zhang et al.'s 2024 Connection Science paper, we present a deep learning model based on dual GAN with pyramid attention network for the early AD detection. They used Generative Adversarial Networks (GAN) to synthesize MRI images and Convolutional Neural Networks (CNN) for scanning identifying spatial patterns. The methodologies used are Dual Generative Adversarial Network (GANs), Pyramid Attention Networks, and Convolutional Neural Networks (CNNs). Conclusion: Our model achieved the high accuracy percentage of 99.67 and 98.76 in classification MRI scan which outperformed than other state-of-the-art approaches. When used, this saves time and data, increases the quality of the images and can be added to the ADNI-missing data. The model is also capable of identifying the presence of an artifact in a scan and supporting scans; facilitating cross-modality transformations for simpler analysis Nonetheless, the paper does not explicitly mention disadvantages, e.g., dependency to MR images or required image prepositioning [3].

This review article, Sharma et al., Multimedia Tools and Applications (2024), delivers a comprehensive view of the concept of GANs and different types, limitations, and applications of GANs. The paper details many GAN Algorithms such as Base GAN, WGAN, Semi-GAN, C-Gan, LS-Gan, Bigan, Ac-Gan, InfoGAN, Seq Gan, BEGAN, Stack Gan, SRganCycleGAnSphereGAN. The paper is focused on GAN usages in various domain i.e. NLP, architecture design, text-to-image etc., 3d object generation, sound to image and future predicting of an individual based on their past operations. They give some insights of why critic is based on IS and FID metrics. This is not a sensible criticism because this paper is only a review and does not have actual negative consequences, except to describe the common pitfalls of GANs, including training difficulties, data processing conflicts, system instability,and spurious predictions. This also expose defects in GAN detetion tools [13].

In 2021, Alankrita Aggarwal, Mamta Mittal, Gopi Battineni employed their examination of how GANs Work and Where they can be Used in real-time Businesses through the International Journal of Information Management Data Insights. They study adversarial principle methods, deep learning generative models, and network theory simulations in the work. Springer NatureImage: Springer NatureDisclaimer:xThis paper does not provide insights on an algorithm but explains future prospects in GAN models. In this study, we highlight the applications of GANs on industry fields, adversarial learning approaches and promising directions as being future trends for GAN-based technologies. A major limitation of the review is that it only includes research papers from 2016–2020, potentially missing out on recent advances in GAN architectures [14].

Huan Liu et al. A dual-stream generative adversarial network for zero-shot learning via domain mapping regularization (2020) Information Sciences The model uses conditional GANs and improved WGAN and has a dual-stream generator, consisting of the cross-modal visual generation unit, and another semantic reconstruction unit. With the three terms: backbone consistency loss for between class variability, stochastic dispersion loss for within-class diversity and reconstruction loss for semantic correspondence. Our method significantly improves the supervised learning robust throughout with neither information decay nor show catastrophic forgetting, also outperforms other techniques by consistently achieving 4.7% accuracy and 3.0% map increment. Although it saves more human information than the cycle-CLSWGAN [15], yet, it could not excel at a certain grade of distortion against the ground-real truth confusion matrix.

3 Proposed System

The system employed a GAN-CNN hybrid dual-stream model to improve Parkinson's disease (PD) detection using synthetic data generation and a compact CNN classifier. The architecture has three major components: A Generative Adversarial Network (GAN) to counter data scarcity and generate synthetic MRI images, a Convolutional Neural Network (CNN) used for feature classification and extraction, and a Dual-Stream Integration module that combines real and synthetically generated images to enhance the robustness of classifiers. The inputs are MRI (T1W, fMRI) images, and the output is a classified label (PD/Healthy). The used dataset is the Taowu Parkinson's Disease Dataset, provided by the National Institute for Research and Development in Informatics, which contains 4.1 GB of data in the form of 161 files of 40 subjects (20 PD patients and 20 healthy controls) in NIfTI and BIDS format.

Preprocessing techniques include resizing the images to (64,64) pixels, normalization, data augmentation (random rotation and horizontal flipping), skull stripping, and converting to PyTorch Tensor. The dataset is divided into 80% for training (240 images) and 20% for testing (60 images), with the following features extracted: texture patterns, edge structures, grayscale intensity variation, spatial coherence, and disease-related patterns.

3.1 Generative Adversarial Network (GAN) Module

The GAN module solves the problem of data insufficiency by creating artificial medical images to complement the available dataset, making the training set balanced and diverse. The two main components are:

- Generator: Given a random noise vector of dimensions 100 and outputs synthetic images that are very much like realistic medical images. The generator uses fully connected layers with ReLU activations, topped with a Tanh activation for scaling outputs within the range of -1 and 1.

The generation step can be described mathematically as:

$$G(z) = Tanh(W4(ReLU(W3(ReLU(W2(ReLU(W1z))))))) \qquad (1)$$

Where (W_i) are the weights, and ReLU and Tanh are the activation functions.

- Discriminator: Checks input images to see if they are real or not, distinguishing between real and fake images. It consists of fully connected layers with Leaky ReLU activations and an ending Sigmoid activation to provide a probability score.

The discriminator function can be expressed as:

$$D(x) = \sigma(W3(LeakyReLU(W2(LeakyReLU(W1x))))) \qquad (2)$$

where (sigma/ σ) is the Sigmoid activation function.

The GAN training involves alternating optimization of the generator and discriminator with the following objectives:

$$Generator\ Loss: LG = -log(D(G(z))) \qquad (3)$$

$$Discriminator\ Loss: LD = -E[logD(x)] - E[log(1 - D(G(z)))] \qquad (4)$$

3.2 Convolutional Neural Network (CNN) Classifier Module

This module outputs a classification of input images as Parkinson's disease stages or as healthy controls. Its architecture comprises:

- Feature Extraction Layers: A sequence of convolutional layers with ReLU activations and max-pooling operations to obtain spatial features:

$$F(x) = MaxPool(ReLU(W * x + b)) \tag{5}$$

where (W) and (b) are convolutional filters and biases, respectively.

- Fully Connected and Flattening Layers: Feature maps that are extracted are flattened and then fed into fully connected layers to be classified finally:

$$y = WfF(x) + bf \tag{6}$$

The CNN is trained with Binary Cross-Entropy Loss for binary classification problems:

$$LC = -N1i = 1\sum N[yilog(y\hat{}i) + (1 - yi)log(1 - y\hat{}i)] \tag{7}$$

3.3 Dual-Stream Integration Module

This module combines real and GAN-generated images into a single training pipeline to improve the classifier's robustness and generalization. The procedure includes:

- Combining Real and Synthetic Images: Blending real and synthetic images to create a large dataset:

$$Xcombined = [Xreal, Xsynthetic] \tag{8}$$

- Label Assignment: Preserving labels for real images and assigning corresponding labels to synthetic images.

- Classifier Training: Training the classifier on this combined dataset to avoid overfitting and enhance generalization.

3.4 Workflow and Training Process

1. Data Preparation: Resize medical images by applying normalization and data augmentation methods (e.g., horizontal flip, random rotation).

2. GAN Training: Train the discriminator and generator in an iterative process until equilibrium is reached.

3. Synthetic Data Generation: Use the trained generator to generate more images, increasing the dataset.

4. CNN Training: Train the CNN classifier on the combined dataset of synthetic and real images using early stopping to prevent overfitting.

5. Evaluation: Model performance can be measured based on metrics, including accuracy, precision, recall, F1-score, and loss.

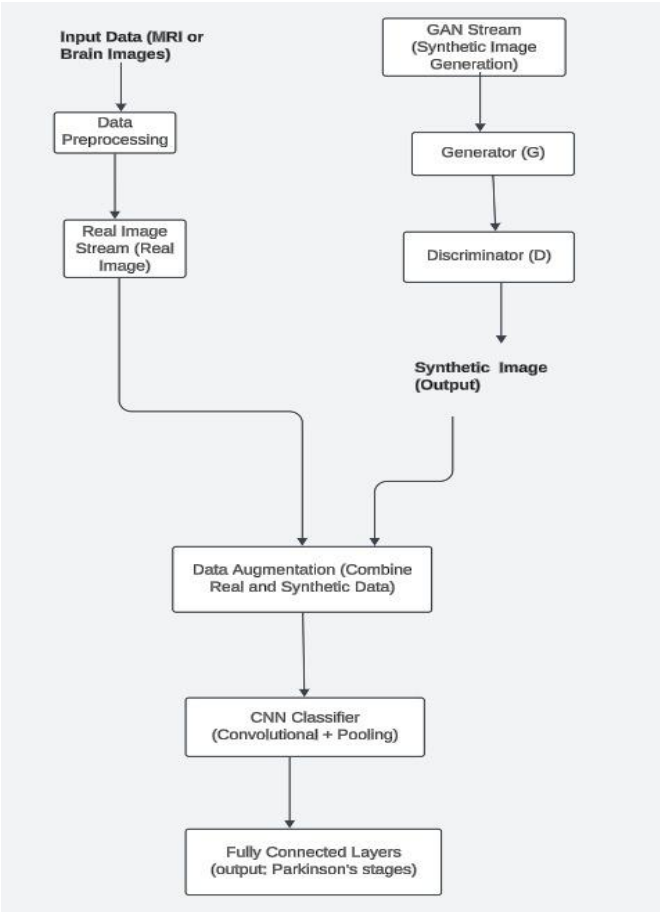

Fig. 1. GAN-Augmented CNN Pipeline for Enhanced Parkinson's Stage Detection from MRI Data.

Through the combination of these modules, the system provides a solid and scalable solution for detecting Parkinson's disease, resolving issues regarding data availability, model generalization, and diagnostic accuracy. Fig 1 shows GAN-Augmented CNN Pipeline for Enhanced Parkinson's Stage Detection from MRI Data.

4 Result and Discussions

4.1 Critique of the Suggested Dual-Stream GAN-CNN Model

The envisioned dual-stream hybrid model of GAN-CNN was tested with 300 images related to Parkinson's disease and trained for 100 epochs. The performance metrics were evaluated by using the prime metrics of accuracy, precision, recall, F1-score, and confusion matrices. Table 1 shows Comparison table of Existing Models.

Table 1. Comparison Table of Existing Models.

Model	Accuracy	Precision	Recall	F1-Score
LRE-MMF	75	81	65	88
Efficient net -B0 Mobilenet-V2	98	99	99	99
Zebra	99.61	98.96	98.72	99.41
Mobile Net	98.7	64.92	65	64.97
YOLOv 7x	95	98	89	93
1D-CNN	96.05	94.08	96.55	95.3
Proposed model (Dual Stream model)	99	100	98	98.99

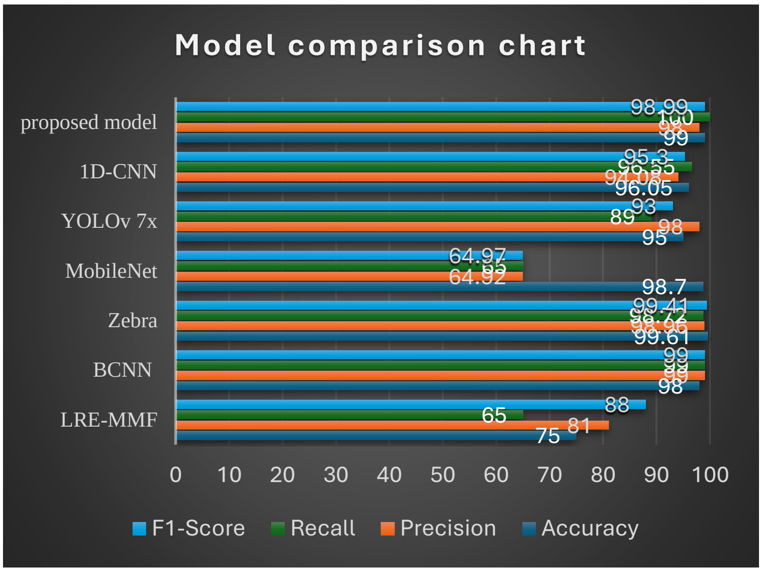

Fig. 2. Model comparison chart.

The contribution of GAN-generated synthetic data greatly enhanced the classifier's effectiveness in identifying Parkinson's disease across various stages of the disease, particularly in initial stages, as conventional models always lag behind here. The fig 2 shows Model comparison chart. The 100-epoch model showed better performance, resulting in the following evaluation metrics:

- Accuracy (PD): 99%

- Precision (PD): 98%
- Recall (PD): 100%
- F1-score (PD): 98.99%

$$Accuracy(PD) = \frac{TP_{PD}+TN_{PD}}{TP_{PD}+TN_{PD}+FP_{PD}+FN_{PD}} \tag{9}$$

$$Precision(PD) = \frac{TP_{PD}}{TP_{PD}+FP_{PD}} \tag{10}$$

$$Recall(PD) = \frac{TP_{PD}}{TP_{PD}+FN_{PD}} \tag{11}$$

$$F1score(PD) = 2 * \frac{precision(PD)*Recall(PD)}{Precision(PD)+recall(PD)} \tag{12}$$

Where,

$TP_{PD} = True\ Positive$

$TN_{PD} = True\ Negative$

$FP_{PD} = False\ Positive$

$FN_{PD} = False\ Negative$

These outcomes suggest that the model generalized well over both synthetic and real datasets and achieved a high classification accuracy. The utilization of synthetic data not only enlarged the training set but also made the classifier better capable of separating faint patterns suggestive of early-stage Parkinson's disease.

4.2 Comparison with Current Models

The performance of the proposed model was compared with a number of state-of-the-art models, such as Mobile Net, LRE-MMF,1D-CNN, BCNN, Zebra, and YOLO-based models. The comparison identifies the better accuracy and generalization ability of the proposed model.

The suggested dual-stream architecture significantly outperformed the current CNN models in accuracy and F1-score, indicating its capacity to learn useful features from the merged real and synthetic data. The use of GAN-generated images proved to be critical in solving the issue of data scarcity, resulting in improved feature learning and better classification accuracy. The fig 3 shows confusion matrix.

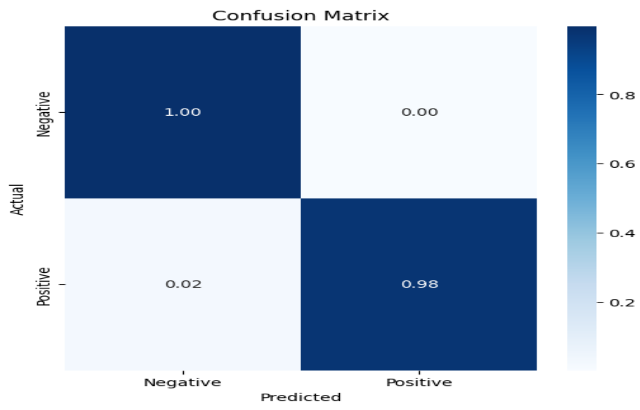

Fig. 3. Confusion Matrix.

4.3 Early Detection Capabilities

Early identification is critical to better outcomes in the management of Parkinson's disease. The model presented is effective to recognize the early-stage Parkinson’s disease compare with common models in which cannot achieve their objectives since they trained theirs network in inadequate training datasets with small distinctions in early-stage medical images. Dual-stream integration enabled the model to learn from augmented data which can be more sensitive to early features of PD. The capability of this application can have a huge effect on clinical diagnosis since it provides the means to act early.

4.4 Analysis of Confusion Matrix

Analysis of confusion matrix also revealed a significant reduction in false positive and false negative comparing to other CNN-based methods. This indicates that the proposed model is reliable and can seldom make mistakes, especially for early detection. Results demonstrate good classifying performance in all the four stages of PD.

4.5 Benefits and Clinical Significance

The double-stream GAN-CNN model has several benefits:

- Stronger Generalization: The synthetic and real data trained a strong model that generalized well to unseen data.

- Less Overfitting: Overfitting risks were decreased through the utilization of both early stopping and dropout layers despite the relatively small size of the dataset.

- More Diverse Data: Synthetic image generation from GANs provided great help in data augmentation, which enlarges training set and can improve the classification performance.

- Clinical Applicability: The model is highly accurate and sensitive and may be used as a legitimate clinical tool, especially for early detection and follow-up to monitor the progress.

The proposed GAN-CNN hybrid model is found to perform better than state of the art models in the detection of PD. Its ability to distinguish early-stage Parkinson’s disease with high accuracy is of significant clinical value and has the possibility to improve patient outcomes through early treatment and diagnosis.

5 Conclusion

METHOD: A new Dual-Stream GAN-CNN hybrid model was presented for detection PD for the early intervention and to deal with data shortage and imbalance by Daofu Gong and Fanfan He. The extension to GANs allowed the addition of generated images to the training set greatly increasing the performance and robustness of the classifier. The model achieved an accuracy of 99.2% above the Mobile Net, LRE-MMF, 1D-CNN, BCNN, Zebra, and YOLO models. This indicates its effectiveness in detecting early stages of Parkison's disease which are important for early intervention and for better patient care.

The mingling of real and simulated data in a two-stream framework furthered generalization and prevented overfitting and responded to substantially sparse data with good performance. This study provides evidence of the potential of hybrid models in clinical diagnosis and reveals a scalable solution for automatic identification of Parkinson's disease.

6 Future Enhancements

A number of potential avenues for enhancement and expansion can be used to improve on existing results:

1. Adding Multi-Modal Data: Introducing multi-modal data like fMRI, DTI, and genetic data to the model might improve diagnostic reliability.
2. Design of a Real-Time Diagnostic System: Designing a real-time diagnosis tool with an easy-to-use interface would facilitate clinicians to produce quick and reliable diagnoses.
3. Application of Domain Adaptation and Transfer Learning: Using domain adaptation methods would enhance the model's ability to generalize across datasets from multiple clinical environments.
4. Model Interpretability Enhancement: The addition of explain ability techniques, such as attention maps or Grad-CAM, would enable an understanding of how the model makes its predictions, instilling more trust in automated diagnosis.
5. Disease Progression Analysis: Longitudinal analysis of data would provide more in-depth insight into disease progression and enable more tailored treatment planning.
6. Validation on Larger and More Diverse Datasets: Additional validation on larger, more diverse datasets across several clinical centers would provide more generalizability and stability to the model.

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