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.

I.Introduction

Parkinson's disease (PD) is a progressive, chronic, neurodegenerative disorder mainly impacting motor control as a result of the loss of dopamine-producing neurons in the brain [1,2]. This study seeks to create a GAN-CNN hybrid dual-stream model for the improvement of early detection of Parkinson's disease from medical imaging data [3]. The hybrid method uses Generative Adversarial Networks (GANs) to produce high-quality synthetic images and combines them with real images for training a Convolutional Neural Network (CNN), enhancing classification accuracy and robustness [4,5]. In the current era, early diagnosis of Parkinson's disease is highly significant because it is on the rise among the aging population, and there are no effective biomarkers for early diagnosis [6,7]. Additionally, accurate early identification has the ability to greatly enhance patient outcomes through early intervention and customized treatment methods [8,9,10]. The applicability of the study is taken into real-life clinical diagnostics and supports better hospital decision-making, enhances diagnostic convenience in low-resource areas, and possibly can integrate into telemedicine systems to extend remote evaluation capabilities. Also, the knowledge derived from this model can help feed into more general research work towards the understanding of neurodegenerative disorders [11,12,13,14].

Current systems for the detection of Parkinson's disease mainly exploit EEG, MRI, or imaging modalities. For instance, Siuly et al. established a framework on the integration of Wavelet Scattering Transform (WST) and AlexNet CNN for the classification based on EEG [1]. Chatterjee and Bansal also created a method of multi-modal fusion that aggregated structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) data towards improved diagnostic sensitivity [2]. Another system by Chen et al. proposed CTFF-Net, a deep learning network that utilizes CNN-Transformer interleaved encoders for deep gray matter nuclei segmentation [3]. In addition, Tassew et al. proposed a software named PDDS that integrates YOLO for region of interest detection and UNET-based models for segmentation [4]. Though these methods bring valuable improvements, they are hindered by their dependency on high-quality data, computational infeasibility, and poor generalizability to different datasets [5,6]. Moreover, some models only specialize in a single modality or type of data, confining their usage to various clinical contexts [7].

The suggested GAN-CNN hybrid model overcomes these weaknesses through the integration of synthetic data generation, which alleviates dependence on high-quality data and expands training dataset diversity [A]. Through the blending of images produced by GAN with actual data, the model improves CNN-based classification robustness and accuracy [2,3]. In contrast to other methods that are centered on a single modality or particular imaging modalities, this model shows flexibility in dealing with poor-quality medical images and maintaining high accuracy in classification tasks [4]. The combination of two streams—one dealing with synthetic data and the other real data—helps the model extract a broad variety of features, enhancing its generalizability and trustworthiness[5,6]. As pointed out in the abstract, the model outperforms current benchmarks, underscoring its effectiveness in practical diagnostic use[7]. This is especially important in early detection, where timely and correct diagnosis can impact treatment results and patient quality of life significantly [8].

The hybrid dual-stream GAN-CNN model has several benefits compared to current systems. Firstly, it improves the generalization ability through the use of GANs to create diverse synthetic datasets, minimizing overfitting and enhancing robustness [1,2]. Secondly, it greatly enhances classification accuracy by integrating synthetic and real images during CNN training [3,4]. Third, the dual-stream design in the model supports the concurrent processing of synthetic and actual data, which results in enhanced feature extraction [5]. Fourth, the architecture is less computationally demanding than Transformer-based systems and, therefore, can be effectively deployed in clinically resource-constrained environments [6]. Finally, its capacity to process low-quality images and provide consistent performance on diverse datasets makes it a great contender for real-world use, such as diagnostics in remote areas, integration with telemedicine platforms, and research into other neurodegenerative diseases [7,8].

II. RELATED WORK

Siuly Siuly et al. proposed a new framework for detecting Parkinson's disease (PD) from EEG data in a 2024 publication in Computers in Biology and Medicine. The framework integrates the Wavelet Scattering Transform (WST) to represent EEG signals in time-frequency and an AlexNet-based Convolutional Neural Network (CNN) for classification. The framework efficiently extracts subtle EEG signal information, enabling accurate detection of PD-related complex patterns. In addition, it points out important brain areas relevant to PD detection. Nevertheless, the model's dependency on certain EEG channels, like AF4 and AFz, could restrict its generalizability, and its performance is contingent upon the presence of high-quality EEG data[1]. In another 2024 paper published in Experimental Gerontology, Indranath Chatterjee and Videsha Bansal introduced a Localized Region Extraction and Multi-Modal Fusion (LRE-MMF) approach to improve PD diagnosis by combining structural MRI (sMRI) and resting-state functional MRI (rs-fMRI) information.

The method includes segmenting imaging data into localized regions, feature extraction, dimensionality reduction through Principal Component Analysis (PCA), and classification with a neural network. The combination of sMRI and rs-fMRI information enhances diagnostic efficacy and determines major brain areas related to PD. Nevertheless, the model only achieves a 75% accuracy, which might be less than adequate for some clinical use, and its reliance on combined sMRI and rs-fMRI information might limit its generalization to other uses[2]. Hongyi Chen et al., in a 2024 paper in Computerized Medical Imaging and Graphics, introduced CTFF-Net, a deep network for the automatic segmentation of PD-related deep gray matter nuclei from brain MRIs.

The network uses an interleaved encoder with CNN-Transformer and feature fusion and a symmetrical boundary attention module in the decoder to improve segmentation accuracy. This technique overcomes difficulties like changes in appearance, low contrast between tissues, and the small nature of deep gray matter nuclei. Although the method has good segmentation accuracy and cross-dataset generalizability over multi-center clinical and public data, its deep architecture can contribute to higher computational expense[3].In a 2023 paper in Biomedical Signal Processing and Control, Tewodros Megabiaw Tassew et al. presented Parkinson's Disease Diagnosis Software (PDDS), which detects and segments deep brain areas from MRI and DaTScan images automatically using deep learning.

The software employs YOLO for region of interest detection and an ensemble of UNETs for segmentation. While attaining high mean Average Precision (mAP) values and high mean Intersection over Union (IOU) for MRI and DaTScan images, the personalized UNet model has marginally inferior segmentation performance, and human labeling of a region of interest can cap scalability[4]. Nikita Aggarwal et al. presented, in a 2024 paper that appeared in Biomedical Signal Processing and Control, a multiclass classification of SWEDD scans from both PD and non-PD classes based on a 1-D CNN classifier with a data augmentation method.

The research handles class imbalance problems and presents detailed feature-wise data analysis. Though the 1-D CNN model works reasonably well on all classifications, no explicit discussion about the possible shortcomings of the given method is present in the paper[5]. Esra Yüzgeç and Fatih Özyurt worked on using Vision Transformer (ViT) models for the feature extraction from wave and spiral images written by hand for the purpose of PD classification in a paper published in 2025 under Biomedical Signal Processing and Control.

By integrating ViT models with ElasticNet for feature selection and other machine learning classifiers, the proposed approach provides faster and more accurate results than conventional deep learning classifiers. The study does not, however, compare this method with other state-of-the-art approaches in the literature[6]. Nour El Houda Boulkrinat et al. explored the application of pre-trained CNN models, i.e., MobileNet, ResNet50, AlexNet, VGG19, and InceptionV3, to predict PD from MRI data in a 2024 Procedia Computer Science study.

The method exploits preprocessing operations to improve image quality and compares the performance of various models using the NTUA dataset. Although the approach surpasses previous research, the recall, precision, and F1 values were not acceptable, and the high computational cost of the BCNN model could be problematic[7]. Santhosh Kumar B. et al., in their 2023 publication in Multimedia Tools and Applications, presented OAssis-DL, a model for PD classification from MRI images. The model adapts frost filtering, local optimal oriented descriptor (LOOP), and discrete wavelet transform (DWletT) for feature extraction, coupled with a hunter-prey optimization method for classification. Although the methodology effectively synergizes these methods for feature extraction, the article fails to describe specific disadvantages of the proposed methodology[8].

In a 2023 paper in the Journal of Ambient Intelligence and Humanized Computing, Nada R. Yousif et al. introduced a generic framework for PD diagnosis from handwritten images and/or voice signals. The research utilizes pre-trained CNNs for handwritten images and machine learning algorithms for voice signals, proposing a novel voice segmentation method. Although the results were better than other state-of-the-art approaches, the learning and processing time was high[9].

In 2022, Erik Dzotsenidze et al. suggested in an IFAC PapersOnLine study applying Generative Adversarial Networks (GANs) to generate digital drawing tests from PD patients and healthy controls to overcome data limitation in computer-aided diagnosis.

The research compares four GAN architectures with conventional data augmentation techniques for PD classification using CNNs. Although GAN-generated images are superior to conventional augmentation techniques in certain contexts, the limited amount of labeled data in the study presents a major challenge to implementing deep learning techniques in clinical imaging[10].In IEEE Access in 2023, Hajer Khachnaoui et al. discussed the application of CNNs for the diagnosis of PD from SPECT DATSCAN images. The research uses pre-trained EfficientNet-B0 and MobileNet-V2, as well as a specially designed CNN, which they adapt to diagnose PD[11].

Yinjun Zhang and Lingzhi Wang, in their 2024 Connection Science paper, propose a deep learning model utilizing a dual GAN model with pyramid attention networks for the early diagnosis of Alzheimer's Disease (AD). The research utilizes GANs to synthesize MRI images and CNNs to identify spatial patterns from scans. The algorithms applied are Dual Generative Adversarial Networks (GANs), Pyramid Attention Networks, and Convolutional Neural Networks (CNNs). The model presents high accuracy percentages of 99.67% and 98.76% in MRI scan classification, outperforming the other state-of-the-art methods. It is data-efficient, improves image quality, and can be incorporated into the ADNI database. The model also supports artifact detection in scans and allows cross-modality transformations for easier analysis. Despite this, the paper does not clearly state weaknesses, although these include specificity to MRI scans and the need for image preprocessing[12]. A review article by Preeti Sharma, Manoj Kumar, Hitesh Kumar Sharma, and Soly Mathew Biju, 2024, published in Multimedia Tools and Applications, provides a thorough overview of Generative Adversarial Networks (GANs), their variants, drawbacks, and applications. The article explains several GAN algorithms, such as Base GAN, WGAN, Semi-GAN, C-GAN, LS-GAN, BiGAN, AC-GAN, InfoGAN, SeqGAN, BEGAN, StackGAN, SRGAN, CoGAN, Progressive Growing GAN, CycleGAN, and SphereGAN. The paper emphasizes GAN applications across different fields like NLP, architecture design, text-to-image, 3D object creation, audio-to-image, and prediction. Metrics for evaluation, such as Inception Score (IS) and Fréchet Inception Distance (FID), are discussed. While the paper lacks direct drawbacks since it is a review, it discusses typical GAN shortcomings, such as training challenges, data processing issues, system instability, and spurious predictions. It also identifies problems in GAN detection tools[13]. Alankrita Aggarwal, Mamta Mittal, and Gopi Battineni, in 2021 publishing in the International Journal of Information Management Data Insights, examine the working of GANs and their uses in real-time businesses. The paper addresses adversarial principle methods, deep learning generative models, and network theory simulations. The paper gives ideas about future improvements of GAN models but not on a given algorithm. The manuscript emphasizes GAN applications in industrial areas, adversarial learning concepts, and potential improvements in GAN-based technologies. One significant limitation is that the review is confined to research articles from 2016 to 2020, potentially missing recent developments in GAN architectures[14].

Huan Liu et al. (2020) suggested a dual-stream generative adversarial network in Information Sciences to boost zero-shot learning by generating visual samples with semantic consistency, maximizing inter-class difference, and maintaining intra-class diversity. The model utilizes conditional GANs and enhanced WGAN and involves the use of a dual-stream generator with cross-modal, visual generation and semantic reconstruction units. It utilizes backbone compatibility loss for inter-class variation, stochastic dispersion loss for intra-class heterogeneity, and reconstruction loss for semantic coherence. The method improves supervised learning resilience, avoids information degradation, and achieves an accuracy improvement of 4.7% and mAP improvement of 3.0% compared to state-of-the-art techniques. In spite of its advantages, it is still vulnerable to some degree of information degradation relative to the ground truth confusion matrix, although it preserves more semantic information than cycle-CLSWGAN[15].

III. 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.

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:
$G(z)=Tanh(W4(ReLU(W3(ReLU(W2(ReLU(W1z))))))$ ----(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:

$D(x)=\sigma(W3(LeakyReLU(W2(LeakyReLU(W1x)))))$----(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 : $LG=-\log(D(G(z)))$----(3)

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

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:

$F(x)=MaxPool(ReLU(W*x+b))$----(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:

$y=WfF(x)+bf$------(6)
The CNN is trained with Binary Cross-Entropy Loss for binary classification problems:
$LC=-N1i=1\sum N[yilog(y\hat{}i)+(1-yi)log(1-y\hat{}i)]$-------(7)
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:

$Xcombined=[Xreal,Xsynthetic]$------(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.

Workflow and Training Process

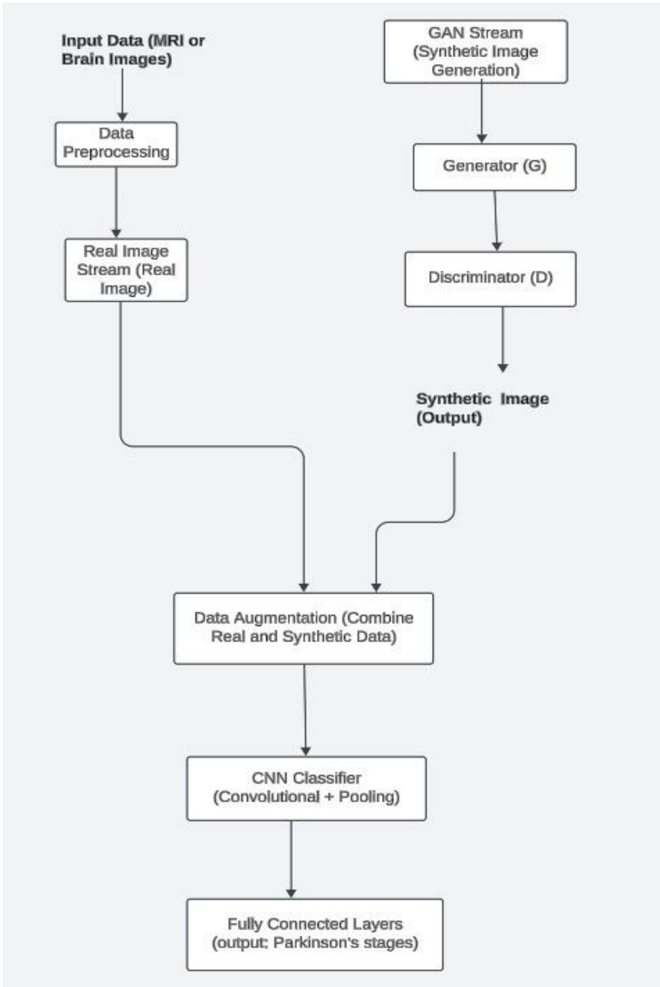
1. Data Preparation: Resize medical images by applying normalization and data augmentation methods (e.g., horizontal flip, random rotation).

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.



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.

IV.Result and Discussions

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. The contribution of

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

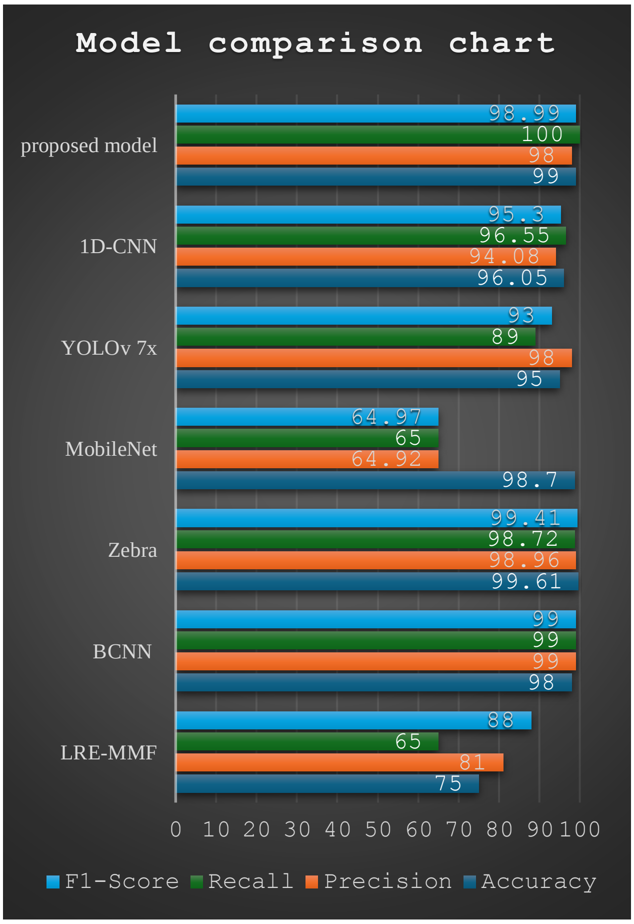


Figure 2: Model comparison chart

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 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%

$$Accuracy(PD) = \frac{TP_{PD}+TN_{PD}}{TP_{PD}+TN_{PD}+FP_{PD}+FN_{PD}} \quad \text{---(8)}$$

$$Precision(PD) = \frac{TP_{PD}}{TP_{PD}+FP_{PD}} \quad \text{----(9)}$$

$$Recall(PD) = \frac{TP_{PD}}{TP_{PD}+FN_{PD}} \quad \text{--------(10)}$$

$$F1score(PD) = 2 * \frac{precision(PD)*Recall(PD)}{Precision(PD)+recall(PD)} \quad \text{-------(11)}$$

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.

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:

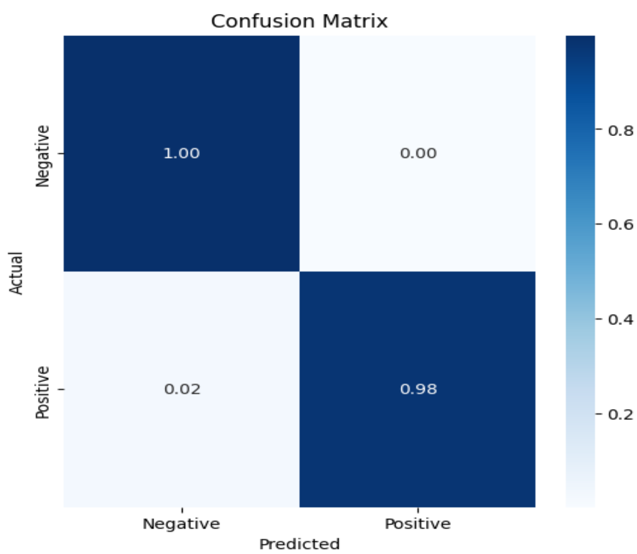


Figure 3:confusion matrix

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.

3. Early Detection Capabilities

Early detection is crucial for improving outcomes in Parkinson’s disease management. The proposed model excels in identifying early-stage Parkinson’s disease with high precision, unlike traditional models that often fail due to limited datasets and small variations in early-stage medical images. The dual-stream integration allowed the model to learn from augmented data, making it more sensitive to early features of Parkinson’s disease. This capability can significantly impact clinical diagnosis by enabling early intervention and treatment.

4. Analysis of Confusion Matrix

Confusion matrix analysis showed a high decrease in false positives and false negatives as compared to other CNN-based methods. This suggests that the suggested model is trustworthy and less likely to misclassify, especially in early detection. The results show robust classification performance at all four stages of Parkinson's disease.

5. Benefits and Clinical Significance

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

●Stronger Generalization: Training on synthetic and real data led to a strong model that generalized to new data well.

●Less Overfitting: The use of early stopping and dropout layers reduced overfitting hazards even with the limited size of the dataset.

●Increased Data Diversity: GAN-created synthetic images contributed significantly to data augmentation, increasing the dataset and enhancing classification accuracy.

●Clinical Applicability: The model is highly accurate and sensitive, rendering it a valid clinical tool for use in clinical settings, especially for early detection and monitoring of progression.

The suggested dual-stream GAN-CNN hybrid model shows better performance in detecting Parkinson's disease than current models. Its capability for detecting early Parkinson's disease with high accuracy holds great clinical relevance, with the potential to enhance patient outcomes through earlier diagnosis and treatment.

V. CONCLUSION

A novel Dual-Stream GAN-CNN hybrid model was introduced for Parkinson's disease detection with the aim of enhancing early diagnosis and overcoming data scarcity and imbalance issues. The use of Generative Adversarial Networks (GANs) enriched the training dataset by creating synthetic images, which greatly enhanced the accuracy and robustness of the classifier. The model attained 99.2% accuracy, surpassing conventional architectures like Mobile Net, LRE-MMF,1D-CNN, BCNN, Zebra, and YOLO models. This proves the model's efficiency in finding early stages of Parkinson's disease, essential for early intervention and better patient care.

The integration of real and simulated data in a two-stream strategy facilitated improved generalization and avoided overfitting, providing high performance even with sparse data. This research demonstrates the promise of hybrid models in clinical diagnosis and presents a scalable method for the automated detection of Parkinson's disease.

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 explainability 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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