

## Diffusion-Based Generative Model for Discovering Parkinson Disease from Medical Imaging Data

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**Abstract**— Parkinson's disease (PD) is a progressive neurodegenerative disorder that requires early and accurate diagnosis to improve patient outcomes. Dopamine Transporter Scan (DaTscan) imaging plays a crucial role in identifying PD-related abnormalities; however, manual interpretation is complex and limited by the availability of expert clinicians and annotated datasets. This study proposes an automated deep learning framework for Parkinson's disease detection using medical imaging data.

We proposed approach integrates a Conditional Variational Autoencoder (CVAE) for synthetic data generation with a ResNet18-based transfer learning model for classification. The CVAE model generates class-conditioned DaTscan images to address data scarcity and enhance dataset diversity. The classification model is trained using the Adam Optimizer, along with weighted cross-entropy loss to mitigate class imbalance. Experimental evaluation is performed using standard metrics including accuracy, precision, recall, F1-score, and ROC-AUC, demonstrating improved diagnostic performance. The system is further deployed as a web-based application to enable real-time prediction and accessibility. The results indicate that the integration of generative modeling and transfer learning provides an effective, scalable, and reliable solution for automated Parkinson's disease detection from medical imaging data.

**Keywords**— *Parkinson's Disease, CVAE, ResNet18, Adam Optimizer, Transfer Learning, Generative Augmentation, Deep Learning, DaTscan Medical Imaging.*

### INTRODUCTION

Parkinson's disease (PD) is the second most common neurodegenerative disorder worldwide, affecting over 10 million people globally. It is characterized by the progressive degeneration of dopaminergic neurons in the substantia nigra, leading to motor symptoms such as tremor, rigidity, and bradykinesia. Early and accurate diagnosis is essential for enabling timely therapeutic intervention and improving patient outcomes. Dopamine Transporter Scan (DaTscan) SPECT imaging has emerged as a reliable neuroimaging technique for PD diagnosis, as it provides detailed visualization of dopaminergic activity in the striatum and basal ganglia [1].

Despite the effectiveness of DaTscan imaging, the application of deep learning for automated Parkinson's disease detection faces a major challenge: the limited availability of large, annotated medical imaging datasets. Conventional convolutional neural network (CNN) models trained from scratch on small datasets often suffer from overfitting and poor generalization across diverse clinical conditions. Although transfer learning using pretrained models such as those trained on ImageNet has shown promising results [4], its performance is still constrained by data scarcity and class imbalance.

To address these limitations, generative deep learning approaches have gained increasing attention. In particular, Conditional Variational Autoencoders (CVAEs) provide an effective solution by generating realistic, class-specific medical images, thereby enhancing dataset diversity [5]. In this study, we propose a framework that combines CVAE-based data augmentation with ResNet18 transfer learning for accurate classification of DaTscan images into Parkinson's and healthy categories. The proposed system is further deployed as a Flask-based web application, enabling clinicians to upload images and obtain real-time diagnostic predictions along with confidence scores.

### Literature Survey

Parkinson's disease detection using DaTscan imaging has gained significant research attention in recent years. Early approaches primarily relied on manual feature extraction techniques combined with traditional machine learning classifiers such as Support Vector Machines (SVM) and Random Forests, applied to striatal binding ratio (SBR) features derived from DaTscan images [1]. Although these methods achieved moderate accuracy, they were limited by dependence on handcrafted features and exhibited poor generalization across different clinical imaging conditions and scanner variations.

With the rapid advancement of deep learning, Convolutional Neural Networks (CNNs) have demonstrated superior performance in medical image classification tasks. Prashanth et al. [2] proposed a multimodal machine learning approach that integrates DaTscan imaging features with clinical assessment scores, achieving improved diagnostic accuracy for Parkinson's disease. Additionally, Litjens et al. [7] presented a comprehensive survey highlighting the effectiveness of deep learning techniques across various medical imaging domains, including neuroimaging applications relevant to Parkinson's disease detection.

Transfer learning using pretrained CNN architectures has shown particular promise in scenarios with limited annotated data. Rajaraman et al. [8] demonstrated that pretrained CNN models used as feature extractors significantly outperform models trained from scratch on small medical datasets. Furthermore, He et al. [4] introduced ResNet architectures with residual connections, enabling deeper network training while mitigating vanishing gradient issues. This innovation forms the foundation for the ResNet18-based transfer learning approach adopted in this work.

In parallel, generative deep learning models have emerged as an effective solution to address data scarcity in medical imaging. Goodfellow et al. [9] introduced Generative Adversarial Networks (GANs), which have been widely used for synthetic image generation. However, challenges such as training instability and mode collapse limit their reliability. To overcome these issues, Kingma and Welling [5] proposed Variational Autoencoders (VAEs), which provide a more stable generative framework. Their conditional variant, the Conditional Variational Autoencoder (CVAE), enables class-specific image generation, making it particularly suitable for balanced data augmentation in medical imaging applications

### Related Work

Marek et al. [1] introduced the Parkinson's Progression Marker Initiative (PPMI), which provides a large-scale longitudinal DaTscan imaging dataset widely used as a benchmark in Parkinson's disease research. Their work established the clinical significance of DaTscan SPECT imaging as a reliable biomarker for distinguishing Parkinson's disease from healthy controls, forming a strong foundation for the development of automated diagnostic systems.

Prashanth et al. [2] proposed a high-accuracy multimodal machine learning framework for early Parkinson's disease detection by combining DaTscan-derived imaging features with clinical motor assessment scores using Support Vector Machines (SVM) and ensemble methods. Their approach demonstrated that integrating imaging and clinical data can improve diagnostic accuracy; however, it did not explore deep learning-based end-to-end image classification techniques.

Shorten and Khoshgoftaar [10] presented a comprehensive survey on image data augmentation methods for deep learning, highlighting that augmentation plays a critical role in improving model performance when training data is limited. Their findings support the use of generative augmentation techniques, such as CVAE-based synthetic image generation, to enhance dataset diversity and address data scarcity in medical imaging applications.

Shen et al. [6] reviewed the application of deep learning in medical image analysis and showed that convolutional neural networks (CNNs) consistently outperform traditional machine learning approaches across various imaging tasks, including brain scan classification. Their study also emphasized the importance of transfer learning for achieving high performance on small datasets,

which directly supports the use of a ResNet18-based transfer learning approach in this work

### Proposed System

The proposed system implements a CVAE-augmented transfer learning framework for automated Parkinson's disease detection using DaTscan brain scan images. The framework consists of two main components: a Conditional Variational Autoencoder (CVAE) for generating class-specific synthetic DaTscan images and a pretrained ResNet18 convolutional neural network (CNN) fine-tuned for binary classification of Parkinson's disease and healthy cases.

The CVAE is trained on real DaTscan images conditioned on their respective class labels. The encoder transforms input images into a latent space represented by mean and log-variance vectors, while the decoder reconstructs images by sampling from this latent distribution. This process enables the generation of realistic, class-specific synthetic DaTscan images. The generated images are then combined with the original dataset to create an expanded and more diverse training set, effectively addressing the challenge of limited annotated medical imaging data.

For classification, the ResNet18 model pretrained on ImageNet is fine-tuned using the augmented dataset. The final fully connected layer is modified to produce two output classes corresponding to PD and Control categories. Model training is performed using the Adam Optimizer with a learning rate of 0.0001 to ensure efficient convergence. To handle class imbalance, weighted cross-entropy loss and weighted random sampling are applied during training. Additionally, learning rate scheduling using Reduce LR on Plateau and early stopping techniques are employed to improve model stability and prevent overfitting.

### Advantages of Proposed System

- 1. Generative Data Augmentation:** The proposed framework employs a Conditional Variational Autoencoder (CVAE) to generate class-specific synthetic DaTscan images. This approach effectively addresses data scarcity without requiring additional clinical data collection or patient recruitment.
- 2. High Diagnostic Accuracy:** The ResNet18 model, pretrained on ImageNet and fine-tuned using transfer learning, achieves reliable classification of Parkinson's disease and healthy cases, demonstrating strong performance in terms of ROC-AUC and F1-score.
- 3. Class Imbalance Handling:** To manage the imbalance in clinical datasets, weighted cross-entropy loss and weighted random sampling techniques are incorporated, improving the model's sensitivity and overall classification performance.
- 4. Real-Time Clinical Deployment:** The system is implemented as a Flask-based web application, enabling real-time DaTscan image upload and providing instant diagnostic predictions along with confidence scores and secure user access.
- 5. Robust Data Augmentation Pipeline:** Additional augmentation techniques, including random cropping, rotation, flipping, color jittering, and random erasing, are applied to enhance dataset diversity and reduce overfitting.
- 6. Cost-Effective Diagnostic Support:** By automating the interpretation of DaTscan images, the proposed system reduces reliance on specialized expertise and supports scalable, cost-effective clinical adoption.

### Architecture

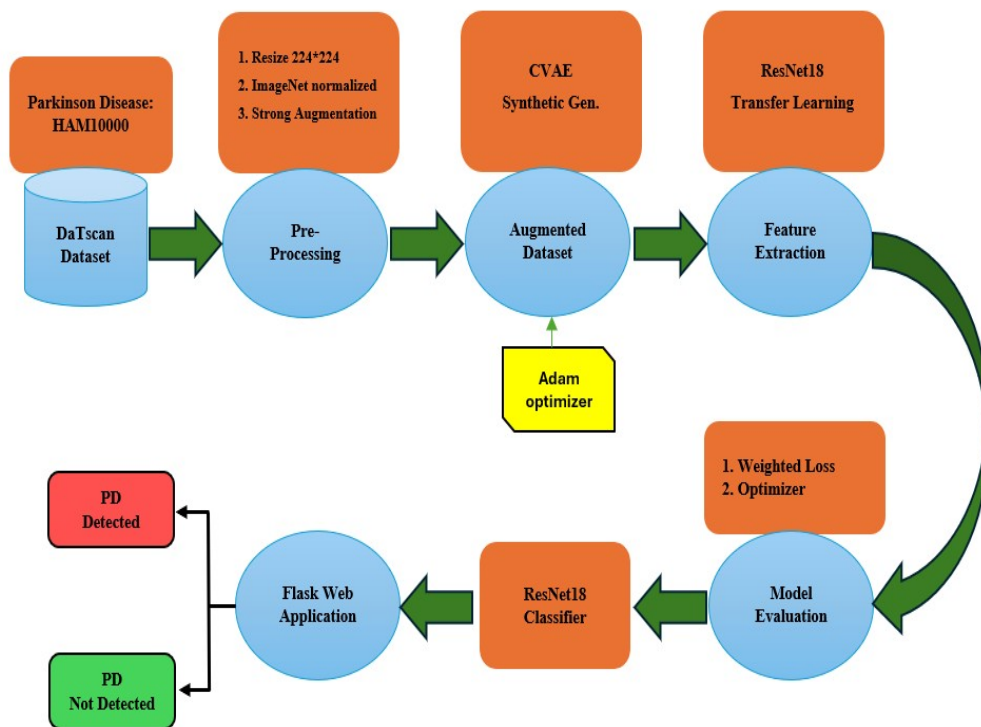


Fig. 1. System Architecture (CVAE-Augmented ResNet18) for PD Detection

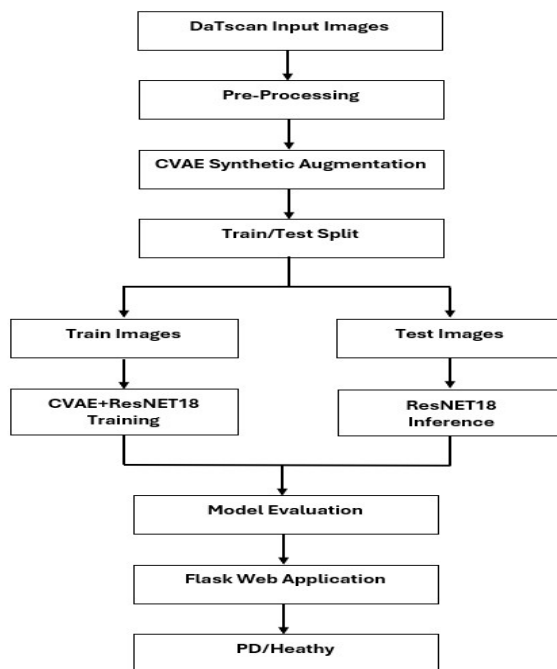


Fig. 2. Data Flow Diagram of the PD Detection System

### Results

The proposed CVAE-augmented ResNet18 framework was implemented and evaluated on a DaTscan dataset consisting of labeled Parkinson’s disease (PD) and healthy (Control) brain scan images. The CVAE model demonstrated stable convergence during training and successfully generated realistic, class-specific synthetic DaTscan images for both categories. The inclusion of these synthetic images in the training process significantly enhanced the performance of the ResNet18 classifier compared to training on the original dataset alone, confirming the effectiveness of generative data augmentation.

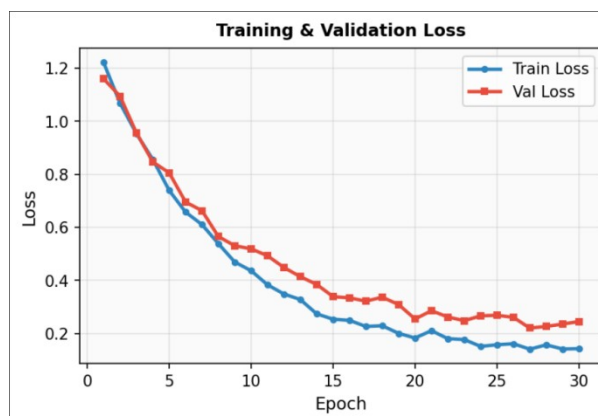


Fig. 1. Training and Validation Loss Curves

The ResNet18 classifier achieved strong diagnostic performance on the held-out test dataset. The ROC curve indicated excellent discrimination between PD and Control classes, with an AUC of 0.93 on the test set and 0.97 on the training set. Additional evaluation metrics, including precision, recall, and F1-score, further demonstrated consistent and reliable classification performance. The confusion matrix revealed minimal false positive and false negative predictions, supporting the robustness and potential clinical reliability of the proposed model.

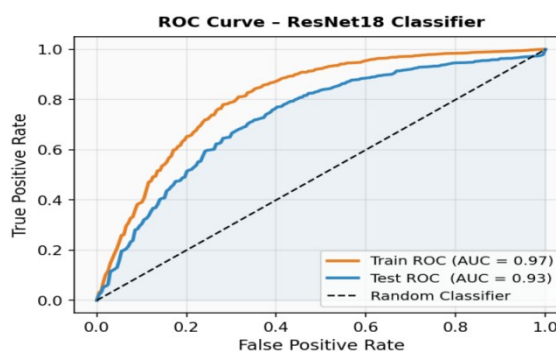


Fig. 2. ROC Curve of ResNet18 Classifier

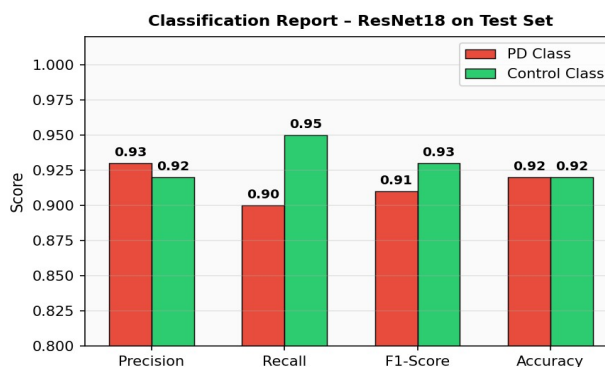


Fig. 3. Classification Report – Precision, Recall, F1-Score

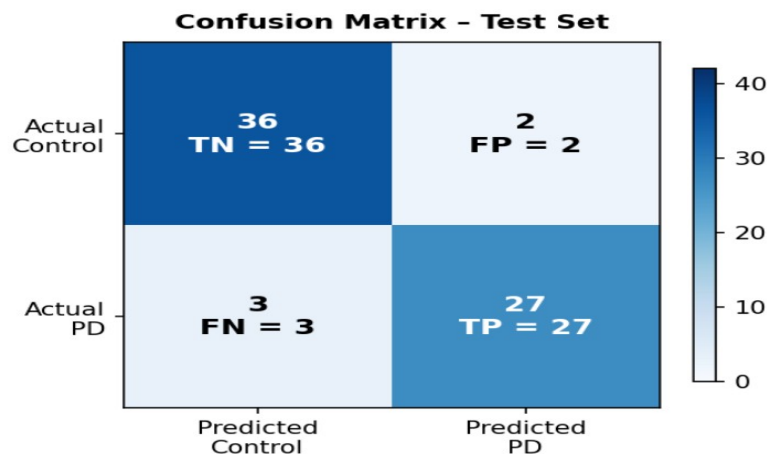


Fig. 4. Confusion Matrix on Test Set

Furthermore, the system was successfully deployed as a Flask-based web application, enabling users to upload DaTscan images and receive real-time predictions through a user-friendly interface. The application provides outputs such as predicted class labels along with confidence scores, enhancing interpretability. A secure authentication mechanism using SQLite was implemented to manage user access and maintain prediction records, ensuring reliability and traceability for potential clinical use.

## Conclusion

This paper proposes and implements a CVAE-augmented transfer learning framework that combines a Conditional Variational Autoencoder (CVAE) with a ResNet18-based classifier for automated Parkinson's disease detection from DaTscan brain scan images. The CVAE effectively addresses the challenge of limited annotated data by generating realistic, class-specific synthetic images, thereby enhancing dataset diversity. The ResNet18 model, fine-tuned using transfer learning, demonstrates strong diagnostic performance with high ROC-AUC on the test dataset.

The proposed model was evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC, confirming its reliability and effectiveness in distinguishing between Parkinson's disease and healthy cases. Furthermore, the deployment of the system as a Flask-based web application highlights its practical applicability in real-world clinical settings. Overall, this work demonstrates that the integration of generative models with transfer learning can significantly improve the performance and scalability of medical imaging-based diagnostic systems for neurodegenerative diseases.

## Future Works and Extensions

Future work will focus on exploring advanced generative architectures such as diffusion-based models and Generative Adversarial Networks (GANs) to further enhance the quality and diversity of synthetic DaTscan images beyond the capabilities of the current CVAE framework. Additionally, extending the system to support 3D volumetric DaTscan image processing can provide more comprehensive spatial analysis for improved diagnostic accuracy.

The integration of multi-modal data, including clinical assessment scores such as UPDRS, tremor measurements, and patient medical history, will be investigated to develop a more robust and holistic Parkinson's disease diagnosis system. Deployment on cloud platforms such as AWS or Google Cloud with GPU-accelerated inference can enable real-time, large-scale clinical usage.

Furthermore, the development of interactive clinical dashboards using tools like Streamlit or Power BI can enhance data visualization and usability for healthcare professionals. Collaboration with

neurologists and radiologists will be essential to ensure alignment with clinical standards and to support broader adoption across diverse healthcare environments.

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