



ParkinNet: a Novel Approach to Classifying Alzheimer's and Parkinson's Diseases Using Brain Structural MRI

Md. Asraf Ali^a, Mejbah Ahammad^a, Nadim Nawshad^a,
Sirajum Munira Shifat^a, M. Firoz Mridha^a, Faysal
Ahmmed^a, and Noor A Jannat Tania^b

^a Dept. of Computer Science, American International University-Bangladesh, 408/1, Kuratoli, Dhaka-1229, Bangladesh

^b Artificial Intelligence Research & Innovation Lab - AIRIL, Dhaka-1207, Bangladesh
✉ asrafali@aiub.edu

KEYWORDS

parkinson's disease;
alzheimer's disease;
deep learning algo-
rithm; classification
algorithm; dementia

ABSTRACT

Both Parkinson's disease (PD) and Alzheimer's disease (AD) are forms of neurodegeneration, which are linked to the same biochemical alterations in the brain. The mixed pathology of these diseases may cause diagnostic dilemmas, which may lead to misdiagnosis. Because of this, classification of AD and PD is essential to reduce extra healthcare costs and the patients' stress. However, the classification of AD and PD can be challenging because of the overlapping symptoms and risk factors. Therefore, the purpose of this study is to develop a model named ParkinNet to classify AD and PD. The current study used Global Average Pooling and Adam optimiser with a batch size of 64. For evaluation, seven deep learning algorithms are used, including MobileNetV2, EfficientNetB2, InceptionResNetv2, VGG16, VGG19, InceptionV3 and ResNet50, along with the proposed ParkinNet model. The proposed ParkinNet model outperforms the other existing models examined in this study and yields an accuracy of 98.54 %. The precise classification of these diseases may contribute to the diagnosis process of AD and PD.

1. Introduction

The brain is the most complex structure of the human body that controls our physical and mental activities, including thought, memory, emotion, motor function, vision, and every movement of our

body (University of Rochester Medical Center, n.d.). The nervous system is responsible for sending and receiving signals throughout the whole body. Dementia is a form of disturbance of the nervous system that affects brain activities. It is a clinical syndrome that causes progressive decline in cognitive abilities. Dementia causes the loss of memory, thinking, and cognitive function. Dementia itself is not a disease, but it is a major symptom of various neurodegenerative conditions, including Alzheimer's disease (AD), Parkinson's disease (PD), frontotemporal dementia (FTD), vascular dementia and many more. In the case of AD, dementia is caused by the accumulation of amyloid plaques and neurofibrillary tangles (Plascencia-Villa and Perry, 2022). In PD, the majority of the people begin to experience movement-related symptoms and up to 80 % of patients eventually develop dementia as the disease progresses, which is linked to the spread of abnormal protein aggregates in the brain. According to a study by the World Health Organisation (WHO), the total number of dementia patients living on the earth is 55 million, which is increasing by 10 million per year (WHO, 2023).

There are diverse types of dementia that affect the human brain, distinguished by the symptoms, and affected region. But the most frequently occurring dementias are PD and AD. Both PD and AD are forms of neurodegeneration that affect the nervous system through the deterioration of brain cells over time (Tong and Chen, 2021; Iravani et al., 2014). The description of AD and PD is given below:

- Alzheimer's disease: AD is the most commonly occurring syndrome among different types of dementia. The symptoms increase over time, beginning with a light memory loss and leading to the loss of the ability to follow even short conversations. The symptoms of AD begin to appear at the age of 60 and become more pronounced around the age of 65 (National Institute of Aging, 2019). AD results in the atrophy or wasting away of brain cells and causes the brain to shrink. These symptoms may also be linked to non-motor symptoms such as dementia, depression, and malfunction in the autonomic nervous system (Kalia and Lang, 2015).
- Parkinson's disease: PD is characterised by movements that are not deliberate or under the control of the patient, and these movements include shaking, rigidity, and trouble with balance and coordination (Tolosa et al., 2006; Yücelbaş, 2021). There are many medical professionals who think that PD is caused by a combination of genetic predisposition and environmental factors, such as exposure to chemicals. Moreover, dopamine insufficiency is the most crucial factor in the development of PD (Sadeghi Razlighi et al., 2012). There is some research which indicates that PD may influence other neurotransmitters, including those that control activities such as blood pressure, digestion, and sweating (Chen et al., 2020; Zesiewicz et al., 2003; Khatri et al., 2020).

There is no evidence showing that one disease may cause the other. Even though PD and AD have a vast number of similar symptoms and risk factors (Compta et al., 2011), there does not seem to be a connection between the two illnesses. Because of the overlapping of the symptoms and disease direction (Sabbagh et al., 2009), the differentiation between PD and AD can be particularly challenging, making the diagnosis process more difficult. On the one hand, PD is identified by motor symptoms including tremors, bradykinesia, and rigidity (Balestrino and Schapira, 2020). On the other hand, AD is identified by progressive memory damage, decline in comprehension capacities and the lack of adaptive functionality (Silva et al., 2019). However, there is a wide range of non-motor symptoms that are identified in both these diseases, such as anxiety, depression, urinary problems and constipation, which further complicates the diagnosis process (Sissons, 2022).

PD treatment in AD patients and the opposite scenario, called mixed pathology, can lead to a major diagnostic dilemma. There is a significant amount of PD patients, who are receiving AD-related

treatments, while a group of AD patients display the pathological hallmark of PD (Xie et al., 2014). The confusion of these pathologies may lead to a misdiagnosis which can negatively affect the patient's treatment outcome. Inappropriate treatment impacts the diagnosis process, resulting in extra healthcare costs and stress in patients.

PD and AD are both diagnosed by medical professionals on the basis of the patient's medical history and neurological examinations (Jankovic, 2008). However, this technique is less accurate because other neurodegenerative illnesses have comparable symptoms (Tolosa et al., 2006). Due to the low accuracy associated with using medical history data, the use of visual image analysis tools is proposed (Berahim et al., 2018). These approaches and tools include brain scans such as computed tomography (CT), magnetic resonance imaging (MRI), or positron emission tomography (PET). Hence, machine learning and more advanced forms of the technique, such as deep learning (DL), have the potential to make major advances in the classification of PD and AD (Zegers et al., 2021).

Therefore, this paper focuses on the classification of PD and AD using a deep neural network model named ParkinNet. A dataset with more than 7000 MRIs has been used to train the model. The dataset was divided into three main classes, namely AD, PD and CONTROL. The dataset was split into train and test sets with a ratio of 70:30. The ParkinNet model excludes the top, fully connected layers and freezes the first 50 layers. This novel approach achieved a significant result of 98.54 %, outperforming other existing DL models, including MobileNetV2, EfficientNetB2, InceptionResNetv2, VGG16, VGG19, InceptionV3 and ResNet50. The current research provides the following contributions:

- A cutting-edge deep learning model specifically designed for the classification of AD and PD using structural MRI data.
- ParkinNet substantially surpasses existing models, mitigating the challenges of overlapping symptoms and risk factors between AD and PD.
- This study stands out for its comparative analysis, assessing the performance of ParkinNet against seven established deep learning algorithms across various metrics.
- The research introduces sophisticated data preprocessing and augmentation methods, including advanced augmentation techniques for structural MRI data.

These novelties position the “ParkinNet” model as a pivotal contributor to the fields of computational neuroscience and medical imaging, offering promising avenues for the early detection and differentiated diagnosis of AD and PD. The model's exceptional accuracy and the methodological advancements presented in this work hold the potential to upscale the approach to neurodegenerative disease management and research.

The rest of the paper is organised as follows. Section 2 describes related work. Section 3 describes the structure and working process of the proposed model. Section 4 compares the results of this study to other studies and elaborates on the performance of the proposed model. Section 5 provides a summary of the entire work and discusses future research.

2. Literature Review

Parkinson's and Alzheimer's diseases have been extensively studied in the past decades. Not only for classification but also for prediction and detection of PD and AD. Many researchers have used

traditional machine learning approaches such as Logistic Regression (LR), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Classifier (SVC), Random Forest (RF), Decision Trees (DT), Gradient Boosting Classifier (GBC), AdaBoost, and XGBoost, and multilayer perceptron to identify AD and PD. DL and other techniques, including CNN, Deep Belief Network (DBN), RNN, DNN, and Support Vector Machine (SVM) have also been used in other studies.

Naseer et al. (2020) used handwriting images to identify PD patients. The authors proposed a deep convolutional neural network classifier that includes strategies for transfer learning and data augmentation to increase the accuracy of the identification. They used ImageNet and the MNIST (Modified National Institute of Standards and Technology database) dataset to examine the freezing and fine-tuning of transfer learning. Another study by Taleb et al. (2020) published the HandPDMultiMC handwriting dataset and studied the use of several DL architectures, such as the CNN and the CNN-BLSTM, to identify PD via the use of time-series classification. A combination of CNN-BLSTM model, trained using jittering and synthetic data augmentation techniques, provided the greatest performance for early PD diagnosis, with an accuracy of 97.62 %. Another group of researchers, Nagasubramanian and Sankayya (2021), developed a DL approach called the deep multivariate vocal data analysis (DMVDA) system to identify the signs and symptoms of PD. They implemented their model with the help of acoustic deep neural networks (ADNNs), acoustic deep recurrent neural networks (ADRNNs), and acoustic deep convolutional neural networks (ADCNNs). In another study, the researchers proposed a framework based on grid search optimization for the development of an optimised DL model for predicting the early onset of PD (Kaur et al., 2020). Within this framework, multiple hyperparameters can be set and tuned for the evaluation of the DL model. The researchers of this study tested their approach using speech samples from PD and healthy individuals and obtained an overall test accuracy of 89.23 % and an average classification accuracy of 91.69 %. Most of the previous research has relied on statistical signal data and hand-crafted features rather than brain scanning images. Sets of brain scanning images, however, are best for the accurate detection of PD and AD.

Jahan et al. (2023) proposed an original explainable AD prediction model by making use of a multimodal dataset. To conduct data-level fusion, the proposed strategy used clinical data, FreeSurfer MRI segmentation data, and psychological data. Another study by Sarica et al. (2022) introduced a machine learning technique called explainable boosting machine (EBM) to discriminate PD from SWEDD by analysing clinical and imaging characteristics. The research by Noor et al. (2020) conducted an in-depth analysis and comparisons of the performances of various existing DL-based methods to detect neurological disorders using MRI data acquired with a variety of modalities, such as structural and functional MRI, with a particular emphasis on AD, PD, and schizophrenia. The above studies only worked to predict or detect the disease. However, the classification of AD and PD plays a vital role in the treatment process and in controlling the progression of these diseases.

In the study of Goyal et al. (2021), a comparison of several different classification techniques, such as SVM (linear, RBF, and polynomial), DT, RF, LR, KNN, NB, Multi-layer Perceptron (MLP), AdaBoost, and XGBoost, was conducted to demonstrate the potential of each classifier for dysphonia-based PD classification. Another study by Martinez-Eguiluz et al. (2023) evaluated the ability of nine different machine learning algorithms to differentiate PD patients from healthy controls using a wide variety of non-motor clinical PD features collected from two different databases: Biocruces (96 subjects) and PPMI (687 subjects). A method for the categorisation of PD was suggested in Mittal and Sharma (2021). This method combines data partitioning with a feature selection procedure known as principal component analysis. The researchers were able to achieve

a classification accuracy of 74.2 %, 85.0 %, and 82.1 % using the logistic algorithm, SVM with the Gaussian classifier, and the weighted k-NN classifier, respectively. Another study by Choi et al. (2020) used fluorodeoxyglucose (FDG)-PET to develop a DL-based cognitive function signature that has the potential to differentiate between PD and AD. The established cognitive signature covers a number of different neurodegenerative illnesses. The research by Kaur et al. (2021) created a feature classification model, based on the AdaBoost and KPCA algorithms, to discover an effective classification of magnetic resonance images of AD and identify an effective classification approach. Another research group developed a technique for identifying magnetic resonance images of healthy individuals and patients with PD using a deep convolution neural network (Fan et al., 2020). These researchers increased the overall amount of training data using a GAN-based data augmentation technique and further used the Alex-Net model, which helped them achieve an average classification accuracy of 89.23 %. To improve the dependability and accuracy of the diffusion tensor imaging (DTI) metrics used for the classification of PD, Prasuhn et al. (2020) have proposed a machine learning algorithm that is more reproducible than manual segmentation of the substantia nigra (SN).

Based on the above literature reviews, it can be concluded that there is a wide range of opportunities to improve the efficiency and accuracy of the classification of PD and AD. A more efficient and accurate model may be developed to increase these parameters.

3. Methodology

This section provides in-depth information on the dataset, the techniques used for data balancing and augmentation, the experimental setup, evaluation metrics, and performance analysis.

We collected the data and built the dataset first. After collecting data, we preprocessed the data using advanced augmentation techniques. Then, we split the dataset into training and test data. The training data is used to train the model, and the test data is used to evaluate the model's performance. When the model failed to achieve optimal accuracy, we fine-tuned the model and re-trained it. After gaining optimal accuracy, we deployed the model for classification. The framework of the proposed ParkinNet model is shown in Figure 1.

3.1. Data Preparation

The dataset of this research was collected from Kaggle, named Alzheimer_Parkinson_Disease, which contains more than 7000 MRIs. We have added some raw images into the dataset as well. The dataset is divided into three classes named AD, PD and CONTROLS. The AD class contains more than 2500 images for the training dataset and more than 600 for testing purposes. For PD, there are around 1000 images for training and 400 for testing purposes. The CONTROL class has around 2800 images for training and more than 600 images for testing. Due to the small number of image samples, augmentation is used before applying DL models to the dataset. Scaling, shifting, flipping, zooming and rotation are the basic data augmentation techniques that are used in this study. While reading the image data, the array value is stored and defined into three categories, namely, CONTROL, PD and AD. Then, the dataset is split into the training and testing sets with a ratio of 70:30 and a data frame is created for both the training and testing sets. Subsequently, we used one-third of the test data for validation.

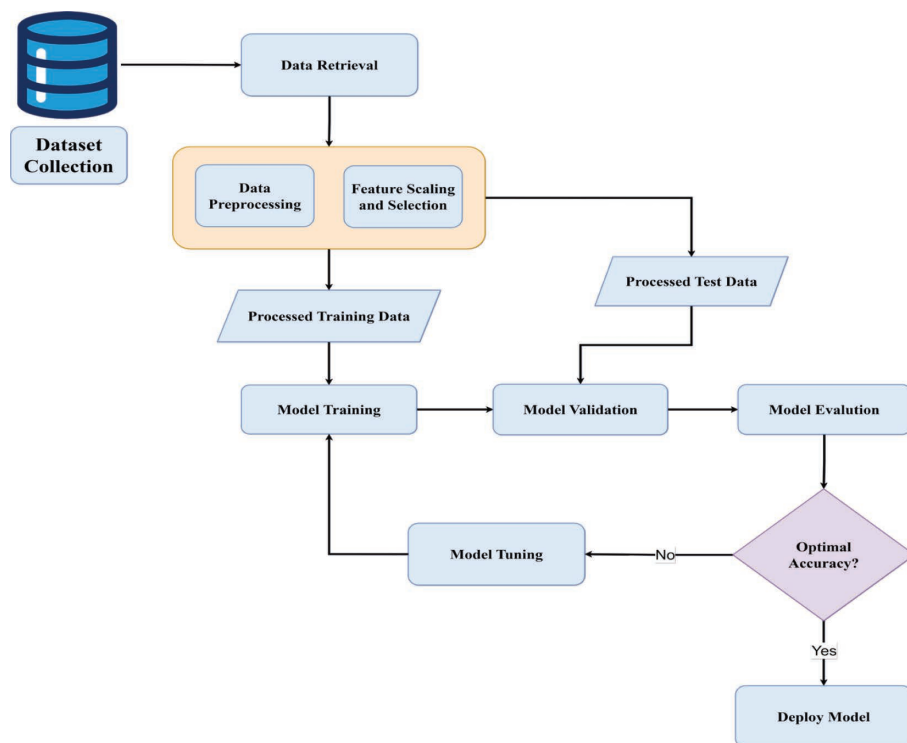


Figure 1. Framework of the proposed ParkinNet model

3.1.1. Data Augmentation

The process of producing new synthetic data from existing data or introducing modest modifications to the current training data is referred to as data augmentation. The method is used to expand the total quantity of data. The input images are horizontally flipped. Similarly, the images are rotated up to a 15-degree angle, and the shift range is set to 15 %. Moreover, we set the zoom range to 15 %. In addition, we used basic data augmentation techniques, including the brightness, contrast, and saturation of the images. The individual data augmentation settings that were considered in this study are presented in Table 1.

3.2. Classification Algorithms

In this experiment, seven existing pre-trained models, including MobileNetV2, EfficientNetB2, InceptionResNetv2, VGG16, VGG19, InceptionV3 and ResNet50, are used to compare the proposed ParkinNet model. The descriptions of the models are given below.

3.2.1. MobileNetV2

MobileNetV2 is the architecture of a convolutional neural network that was created specifically for use in mobile devices. This architecture is constructed with an inverted residual structure, and residual

Table 1. Data augmentation settings

Data augmentation method	Parameter Action value	Action
rotation_range	15	The image is rotated randomly up to 15 degrees to simulate varied orientations
zoom_range	0.15	The image is randomly zoomed in or out by up to 15 % to simulate camera movement
width_shift_range	0.15	The image is horizontally shifted by up to 15 % of the width to mimic lateral movement.
height_shift_range	0.15	The image is vertically shifted by up to 15 % of the height to replicate vertical motion
shear_range	0.1	The image undergoes a shear transformation of up to 10 % to simulate perspective distortions
preprocess_input	Xception default	The pixel values are normalised as per the Xception model's expected input format
horizontal_flip	True	There is a one in two chance that the image will be flipped horizontally

connections are established between the bottleneck levels. Lightweight depth-wise convolutions are used inside the intermediate expansion layer filters and serve the purpose of providing a nonlinear effect. After the first complete convolution layer in the design of MobileNetV2, which has 32 filters, there are 19 layers that are considered residual bottlenecks (Sandler et al., 2018). The MobileNetV2 is highly efficient for mobile devices, but it can provide less accuracy.

3.2.2. EfficientNetB2

EfficientNet is the architecture for convolutional neural networks. It is a scaling technique that employs the use of a compound coefficient to scale all depth, breadth, and resolution parameters consistently. The EfficientNet scaling approach scales the network width, depth, and resolution evenly by using a defined set of scaling coefficients. When scaling network width, depth, and resolution, EfficientNet uses a compound coefficient to ensure that the scaling is performed in a uniform and consistent manner. For the purpose of categorisation in the current investigation, EfficientNet B2 is used. EfficientNetB2 achieves excellent accuracy with fewer parameters, but it is difficult to customise. The design of EfficientNet-B2 is the same as that of EfficientNet-B0; the only change is that the number of feature maps, also known as channels, results in an increase in the number of parameters (Tan and Le, 2019).

3.2.3. Inception-ResNet-v2

Inception-ResNet-v2 is a convolutional neural architecture with 467 layers and extends the Inception family of architectures by incorporating residual connections in place of the filter concatenation stage found in the Inception architecture. It combines high accuracy with residual connections but is computationally intensive. It extends the capabilities of the Inception family of architectures. This

architecture uses factorisation to decrease the size of the filter, which in turn reduces the amount of overfitting that occurs (Szegedy et al., 2017).

3.2.4. VGG-16

VGG-16 architecture is a DL model that represents CNN structure with 16 convolutional and fully connected layers. The stride size of this design is 1 and is characterised by a convolutional filter of 3×3. The size of input images, processed in VGG16, is 224×224. A total of 512 channels is utilised to proceed with the fully connected layers. The feature map with 7×7 dimension is converted into a vector with channels of 25,088 (Faisal et al., 2021). VGG-16 is simple and easy to fine-tune, but it has a large number of parameters with lower computational efficiency.

3.2.5. VGG-19

The architecture of the VGG neural network is a classic example of a convolutional neural network architecture and is based on an investigation of the many methods available for expanding such networks. The VGG-19 network has three more layers than the VGG-16 network and thus has a total of 19 layers for learning weight and bias factors. In all the layers, 3×3 convolutional filters are used to make the architecture more efficient. Moreover, the max-pooling layers decrease the feature dimensions and chances of overfitting (Jaworek-Korjakowska et al., 2019). Though VGG-19 offers slightly better accuracy than VGG-16, it uses more parameters, which makes it heavier and slower.

3.2.6. InceptionV3

An Inception network is a type of deep neural network with an architectural design composed of components that are repeated several times and are referred to as Inception modules. The study used a convolutional neural network architecture called InceptionV3 from the Inception family. This architecture makes use of label smoothing, factorised 7 x 7 convolutions, and an auxiliary classifier to propagate label information down the network. Additionally, batch normalisation was utilised for the layers in the sidehead (Szegedy et al., 2016). InceptionV3 balances accuracy and computational efficiency by using factorised convolutions and auxiliary classifiers, but its complex architecture can make customisation and implementation more challenging.

3.2.7. ResNet50

A variation of the ResNet model known as ResNet50 has 48 convolution layers, one max pooling layer and one average pooling layer and can perform 3.8×10^9 operations at the floating-point level. A convolution and an identity block may be found at each stage of the ResNet-50 model, which has five stages. Each convolution block has three identity block layers and three convolution layers. ResNet50 addresses vanishing gradients through skip connections but remains heavy for real-time use. Its architecture provides more than 23 million trainable parameters to the researcher's disposal (Pradhan et al., 2023).

3.3. Proposed Model

We used a fine-tuned convolutional neural network based on the Xception model. We reshaped the dataset images to (224, 224, 3) and passed them into the Xception base model. To improve the

performance of the model, we removed the top fully connected layers and froze the first 50 layers of the Xception model. We used cross-validation with five k-folds and an independent hold-out cohort. Furthermore, we used a global average pooling layer that converted the spatial feature maps into a 1D vector. After that, we normalised the images by using Batch Normalisation and regularised with a Dropout layer (rate 0.5). Then, we added a Dense layer with 64 ReLU-activated units and incorporated L2 regularization. After the Dense Layer, we added another Dropout layer with a rate of 0.3. We used a softmax activation function at the final output layer to predict class probabilities across the number of target labels. We utilised the Adam optimiser with a learning rate scheduler based on CosineDecayRestarts, configured with an initial learning rate of 0.001, dynamic decay steps, and gradual minima. To avoid overfitting, we used an EarlyStopping callback that monitors validation loss with a patience of 10 epochs and set restore_best_weights to true. To evaluate the performance of the ParkinNet model, we used various metrics, including Accuracy, Precision, Recall, AUC, and a custom F1 Score to ensure robust classification. Figure 2 shows the architecture of the proposed ParkinNet model.

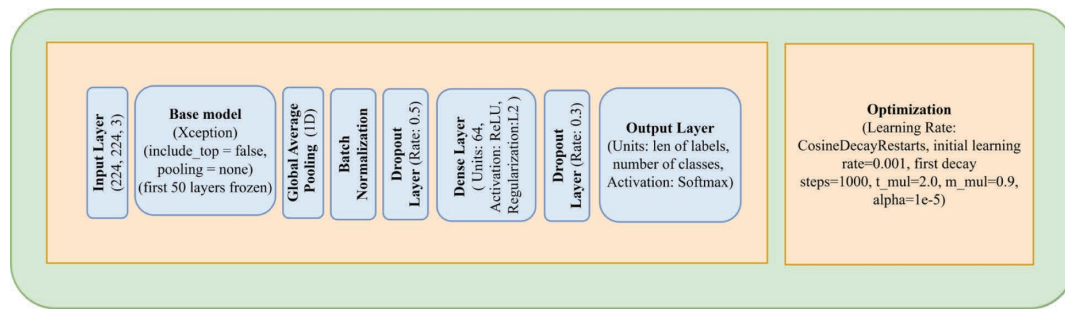


Figure 2. Architecture of the proposed ParkinNet model

The following are the factors that were used in the training of the proposed ParkinNet model:

- Epochs: 50
- Optimiser: Adam
- Learning rate: 0.001
- Batch size: 64
- Time per epoch: 111s
- Training & testing set split ratio: 70 %: 30 %
- Train tensor shape: (8400, 224, 224, 3)
- Test tensor shape: (3600, 224, 224, 3)

The study has utilised some of the most prominent testing methods, including the confusion matrix of positive and negative rates, misclassified, ROC curve, and cumulative gain to validate and evaluate the performance and experience of the proposed model, ParkinNet. The following metrics were generated and assessed during the performance evaluation of the trained model using testing samples: precision, recall, F1-score, and accuracy. Brain scanning images that have not been altered in any way were utilised

as samples for testing. The objective of this analysis was to evaluate the performance of the model. The mathematical models used to determine these metrics are presented in equations 1, 2, 3 and 7.

$$Accuracy (ACC) = \frac{TP}{TP+TN+FP+FN} \quad (1)$$

$$Precision (PRE) = \frac{TP}{TP+FP} \quad (2)$$

$$Recall (REC) = \frac{TP}{TP+FN} \quad (3)$$

$$f1-score = 2 * \frac{TP}{2*TP+FP+FN} \quad (4)$$

The words “true positive” (TP) and “true negative” (TN) refer to the number of positive and negative samples that have been successfully recognised in these computations, respectively. In addition, the numbers of positive and negative samples that were discovered are reflected by the terms “false positive” (FP) and “false negative” (FN). In contrast, the numbers of positive and negative samples that have been recognised are indicated by the terms “false positive” (FP) and “false negative” (FN), respectively. The model made the confusion matrix by emphasising the non-zero integers in ascending order with increases in the colouring order and colour density, which significantly enhanced the readability. Figure 3 shows the confusion matrix of the proposed model.

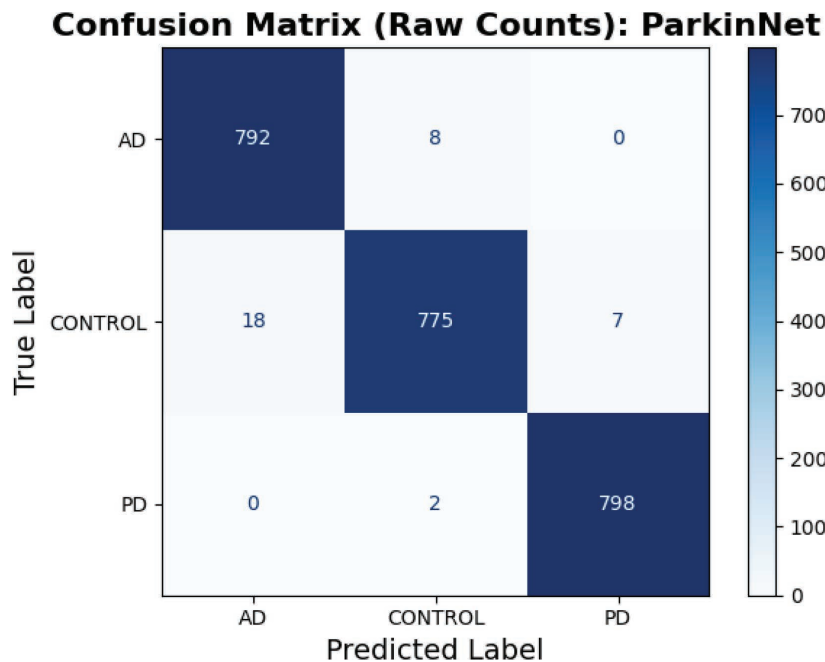


Figure 3. Confusion Matrix of the proposed ParkinNet model

4. Results and Analysis

This section presents the results of this study and describes the analysis of the performance of the proposed ParkinNet model. Additionally, the current study presents the comparisons of the ParkinNet model with the other existing models examined in this study.

This research endeavour culminated in the development of ParkinNet, a novel deep learning model that significantly outstrips the diagnostic performance of existing algorithms in terms of classifying AD and PD. Upon rigorous testing and validation, ParkinNet demonstrated an unparalleled classification accuracy of 98.54 %, thereby establishing a new benchmark in the domain of neurodegenerative disease diagnostics. The comparative analysis encompassed seven other state-of-the-art deep learning models, including MobileNetV2, EfficientNetB2, InceptionResNetv2, VGG16, VGG19, InceptionV3 and ResNet50, with accuracy ranging from 77.17 % to 96.42 %. The performance of various models, which are examined in this study, is presented in Table 2.

Notably, the VGG16 model provided the least accurate predictions of 77.17 %. EfficientNetB2 emerged as the most competitive existing model with an accuracy of 96.42 %. EfficientNetB2 was able to achieve this improved performance because of the balanced scaling method of convolution layers and the use of efficient attention mechanisms. Figure 4 presents the accuracy vs loss curves of VGG16 and EfficientNetB2.

Table 2 shows that the existing models, examined by this study, were substantially surpassed by the proposed ParkinNet model. The performance of the proposed ParkinNet model in different classes is presented in Table 3. The table shows the overall performance of the model per class. During the

Table 2. Evaluation results of various examined models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC (%)
VGG-16	77.17	76.41	77.17	76.46	89.32
VGG-19	78.42	83.57	78.42	75.51	90.73
ResNet50	79.92	80.23	79.92	78.80	91.60
MobileNetV2	84.25	86.22	84.25	84.60	96.79
InceptionV3	85.25	84.94	85.25	84.95	95.87
Inception-ResNet-v2	86.50	86.55	86.50	86.18	96.27
EfficientNetB2	96.42	96.48	96.42	96.42	99.72
ParkinNet (Proposed)	98.54	98.54	98.54	98.54	99.84

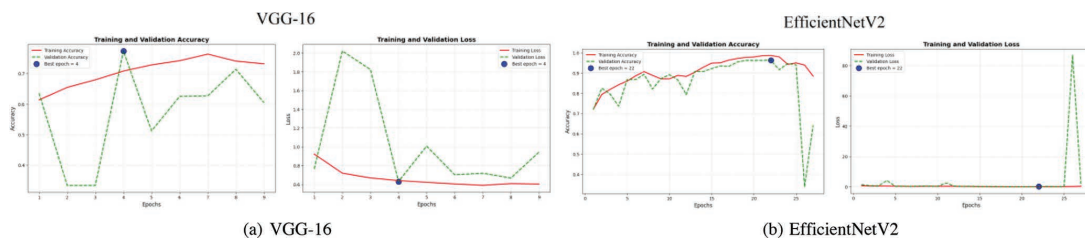


Figure 4. Accuracy and loss curves of VGG-16 and EfficientNetV2 examined in this study

Md. Asraf Ali, Mejbah Ahammad, Nadim Nawshad,
Sirajum Munira Shifat, M. Firoz Mridha, Faysal
Ahmed, and Noor A Jannat Tania

ParkinNet: a Novel Approach to Classifying Alzheimer's
and Parkinson's Diseases Using Brain Structural MRI



ADCAIJ: Advances in Distributed Computing
and Artificial Intelligence Journal
Regular Issue, Vol. 14 (2025), e32178
eISSN: 2255-2863 - <https://adcaij.usal.es>
Ediciones Universidad de Salamanca - CC BY-NC-ND

Table 3. Performance of the proposed ParkinNet model in different labels

Label	Precision	Recall	F1-Score	Support
AD	0.98	0.99	0.98	800
PD	0.99	0.97	0.98	800
CONTROL	0.99	1.00	0.99	800
Accuracy	0.9854			2400
Macro Average	0.99	0.99	0.99	2400
Weighted Average	0.99	0.99	0.99	2400

evaluation, the lowest value was counted for the Recall of Control of 0.97, while most of the parameters achieved the top value of 1.00.

The accuracy of our proposed ParkinNet model improves at a rapid rate throughout the training process until the 7th epoch. Then, a little dip is shown and improves at a reasonable pace until the 24th epoch. A comparable decline in loss was also observed at approximately the opposite rate. The best accuracy is recorded for the 24th epoch of 98.54 %. And the best epoch for loss was the 25th epoch. The accuracy vs validation loss graphs in Figure 5 show both the training and validation data of the proposed ParkinNet model.

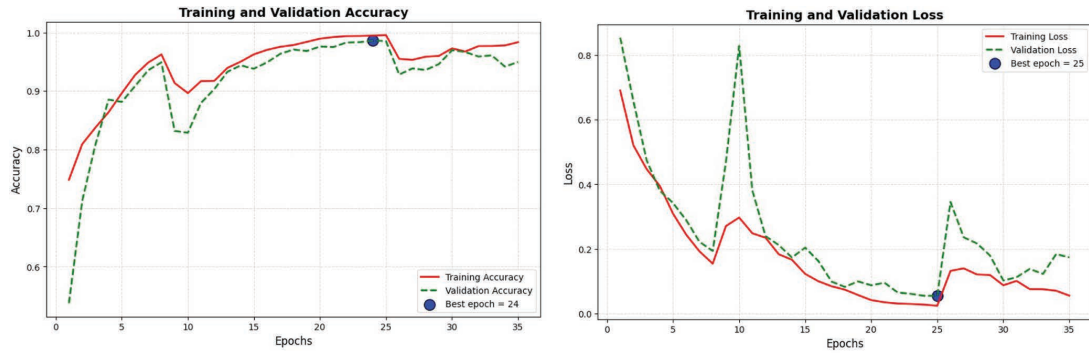


Figure 5. Accuracy and loss curves of the proposed ParkinNet model for both the training and testing data

5. Conclusion

Overall, distinguishing between AD and PD is a considerable challenge because of a wide range of overlapping symptoms and risk factors. Therefore, this study introduced a classification model named ParkinNet to classify PD and AD. The ParkinNet model includes advanced augmentation techniques, deep learning techniques and Adam optimisation. The RAM was observed both before and during the model evaluation on the training and target platforms, which revealed good runtime and memory utilisation results. Despite the promising result, this study has some limitations. We only used 2D MRI slices,

while 3D slices may improve the model's ability to capture spatial relationships and subtle volumetric changes that are critical for diagnosis. Moreover, the study was conducted on a single imaging modality without incorporating other valuable clinical, genetic, or functional data. In the future, investigations might be conducted into a broader array of trainable parameters, exploring more variables and refining processing methodologies to bolster the model's learning efficiency. Such endeavours could further elevate the model's diagnostic precision and operational efficiency, solidifying its utility in clinical practice.

Acknowledgements

The authors would like to express their gratitude to American International University - Bangladesh for providing the most conducive research environment.

References

- Balestrino, R., & Schapira, A. (2020). Parkinson disease. *European Journal of Neurology*, 27(1), 27–42. <https://doi.org/10.1111/ene.14108>
- Berahir, M., Samsudin, N. A., & Nathan, S. S. (2018). A review: Image analysis techniques to improve labeling accuracy of medical image classification. In *Recent Advances on Soft Computing and Data Mining* (pp. 298–307). Springer. https://doi.org/10.1007/978-3-319-76351-4_29
- Chen, Z., Li, G., & Liu, J. (2020). Autonomic dysfunction in Parkinson's disease: Implications for pathophysiology, diagnosis, and treatment. *Neurobiology of Disease*, 134, 104700. <https://doi.org/10.1016/j.nbd.2019.104700>
- Choi, H., Kim, Y. K., Yoon, E. J., Lee, J.-Y., Lee, D. S., & Alzheimer's Disease Neuroimaging Initiative. (2020). Cognitive signature of brain FDG PET based on deep learning: Domain transfer from Alzheimer's disease to Parkinson's disease. *European Journal of Nuclear Medicine and Molecular Imaging*, 47, 403–412. <https://doi.org/10.1007/s00259-019-04526-3>
- Compta, Y., Parkkinen, L., O'Sullivan, S. S., Vandrovicova, J., Holton, J. L., Collins, C., Lashley, T., Kallis, C., Williams, D. R., de Silva, R., & Lees, A. J. (2011). Lewy- and Alzheimer-type pathologies in Parkinson's disease dementia: Which is more important? *Brain*, 134(5), 1493–1505. <https://doi.org/10.1093/brain/awr098>
- Faisal, A., Dharma, T. N. A., Ferani, W., Widi, P. G., & Rizka, S. F. (2021). Comparative study of VGG16 and MobileNetV2 for masked face recognition. *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, 6(2), 230–237. <https://doi.org/10.26555/jiteki.v6i2.21120>
- Fan, Z., Xu, F., Li, C., & Yao, L. (2020). Application of KPCA and AdaBoost algorithm in classification of functional magnetic resonance imaging of Alzheimer's disease. *Neural Computing and Applications*, 32, 5329–5338. <https://doi.org/10.1007/s00521-018-3523-4>
- Goyal, J., Khandnor, P., & Aseri, T. C. (2021). A comparative analysis of machine learning classifiers for dysphonia-based classification of Parkinson's disease. *International Journal of Data Science and Analytics*, 11, 69–83. <https://doi.org/10.1007/s41060-020-00224-4>
- Iravani, B., Towhidkhah, F., & Roghani, M. (2014). A new feature extraction method and classification of early stage parkinsonian rats with and without DBS treatment. *Australasian Physical & Engineering Sciences in Medicine*, 37, 655–664. <https://doi.org/10.1007/s13246-014-0305-9>

- Jahan, S., Abu Taher, K., Kaiser, M. S., Mahmud, M., Rahman, M. S., Hosen, A. S., & Ra, I.-H. (2023). Explainable AI-based Alzheimer's prediction and management using multimodal data. *PLOS ONE*, 18(11), e0294253. <https://doi.org/10.1371/journal.pone.0294253>
- Jankovic, J. (2008). Parkinson's disease: Clinical features and diagnosis. *Journal of Neurology, Neurosurgery & Psychiatry*, 79(4), 368–376. <https://doi.org/10.1136/jnnp.2007.131045>
- Jaworek-Korjakowska, J., Kleczek, P., & Gorgon, M. (2019). Melanoma thickness prediction based on convolutional neural network with VGG-19 model transfer learning. *CVPR Workshops*, 0–0. https://openaccess.thecvf.com/content_CVPRW_2019/html/CVPM/Jaworek-Korjakowska_Melanoma_Thickness_Prediction_Based_on_Convolutional_Neural_Network_With_CVPRW_2019_paper.html
- Kalia, L. V., & Lang, A. E. (2015). Parkinson's disease. *The Lancet*, 386(9996), 896–912. [https://doi.org/10.1016/S0140-6736\(14\)61393-3](https://doi.org/10.1016/S0140-6736(14)61393-3)
- Kaur, S., Aggarwal, H., & Rani, R. (2020). Hyper-parameter optimization of deep learning model for prediction of Parkinson's disease. *Machine Vision and Applications*, 31, 1–15. <https://doi.org/10.1007/s00138-020-01068-4>
- Kaur, S., Aggarwal, H., & Rani, R. (2021). Diagnosis of Parkinson's disease using deep CNN with transfer learning and data augmentation. *Multimedia Tools and Applications*, 80(7), 10113–10139. <https://doi.org/10.1007/s11042-020-10150-4>
- Khatri, D. K., Choudhary, M., Sood, A., & Singh, S. B. (2020). Anxiety: An ignored aspect of Parkinson's disease lacking attention. *Biomedicine & Pharmacotherapy*, 131, 110776. <https://doi.org/10.1016/j.biopha.2020.110776>
- Martinez-Eguiluz, M., Arbelaitz, O., Gurrutxaga, I., Muguerza, J., Perona, I., Murueta-Goyena, A., Acera, M., Del Pino, R., Tijero, B., & Gomez-Esteban, J. C. (2023). Diagnostic classification of Parkinson's disease based on non-motor manifestations and machine learning strategies. *Neural Computing and Applications*, 35(8), 5603–5617. <https://doi.org/10.1007/s00521-022-07651-3>
- Mittal, V., & Sharma, R. (2021). Machine learning approach for classification of Parkinson disease using acoustic features. *Journal of Reliable Intelligent Environments*, 7(3), 233–239. <https://doi.org/10.1007/s40860-021-00134-9>
- Nagasubramanian, G., & Sankayya, M. (2021). Multivariate vocal data analysis for detection of Parkinson disease using deep learning. *Neural Computing and Applications*, 33(10), 4849–4864. <https://doi.org/10.1007/s00521-020-05358-3>
- Naseer, A., Rani, M., Naz, S., Razzak, M. I., Imran, M., & Xu, G. (2020). Refining Parkinson's neurological disorder identification through deep transfer learning. *Neural Computing and Applications*, 32(3), 839–854. <https://doi.org/10.1007/s00521-018-3933-3>
- National Institute of Aging. (2019). What causes Alzheimer's disease? <https://www.nia.nih.gov/health/alzheimers-causes-and-risk-factors/what-causesalzheimers-disease>
- Noor, M. B. T., Zenia, N. Z., Kaiser, M. S., Mamun, S. A., & Mahmud, M. (2020). Application of deep learning in detecting neurological disorders from magnetic resonance images: A survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia. *Brain Informatics*, 7, 1–21. <https://doi.org/10.1186/s40708-020-00112-2>
- Plascencia-Villa, G., & Perry, G. (2022). Neuropathologic changes provide insights into key mechanisms of Alzheimer disease and related dementia. *The American Journal of Pathology*, 192(10), 1340–1346. <https://doi.org/10.1016/j.ajpath.2022.06.006>

- Pradhan, A. K., Mishra, D., Das, K., Obaidat, M. S., & Kumar, M. (2023). A COVID-19 X-ray image classification model based on an enhanced convolutional neural network and hill climbing algorithms. *Multimedia Tools and Applications*, 82(9), 14219–14237. <https://doi.org/10.1007/s11042-022-13459-7>
- Prasuhn, J., Heldmann, M., Münte, T. F., & Brüggemann, N. (2020). A machine learning-based classification approach on Parkinson's disease diffusion tensor imaging datasets. *Neurological Research and Practice*, 2, 1–5. <https://doi.org/10.1186/s42466-020-00052-6>
- Sabbagh, M. N., Adler, C. H., Lahti, T. J., Connor, D. J., Vedders, L., Peterson, L. K., Caviness, J. N., Shill, H. A., Sue, L. I., Ziabreva, I., & Beach, T. G. (2009). Parkinson disease with dementia: Comparing patients with and without Alzheimer pathology. *Alzheimer Disease & Associated Disorders*, 23(3), 295–297. <https://doi.org/10.1097/WAD.0b013e3181a6be30>
- Sadeghi Razlighi, M., Jafari, A. H., Firoozabadi, S. M., & Shahidi, G. A. (2012). Study of chaotic behavior of tremor of some Parkinsonians under deep brain stimulation. *Australasian Physical & Engineering Sciences in Medicine*, 35, 25–30. <https://doi.org/10.1007/BF03321839>
- Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 4510–4520). <https://doi.org/10.1109/CVPR.2018.00474>
- Sarica, A., Quattrone, A., & Quattrone, A. (2022). Explainable machine learning with pairwise interactions for the classification of Parkinson's disease and SWEDD from clinical and imaging features. *Brain Imaging and Behavior*, 16(5), 2188–2198. <https://doi.org/10.1007/s11682-021-00562-2>
- Silva, M. V. F., Loures, C. d. M. G., Alves, L. C. V., de Souza, L. C., Borges, K. B. G., & Carvalho, M. d. G. (2019). Alzheimer's disease: Risk factors and potentially protective measures. *Journal of Biomedical Science*, 26, 1–11. <https://doi.org/10.1186/s12929-019-0524-y>
- Sissons, B. (2022). *What is the difference between Parkinson's disease and Alzheimer's disease?* <https://www.medicalnewstoday.com/articles/parkinsons-vs-alzheimers>
- Szegedy, C., Ioffe, S., Vanhoucke, V., & Alemi, A. (2017). Inception-v4, inception-resnet and the impact of residual connections on learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, 31(1). <https://doi.org/10.1609/aaai.v31i1.11231>
- Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 2818–2826). <https://doi.org/10.1109/CVPR.2016.308>
- Taleb, C., Likforman-Sulem, L., Mokbel, C., & Khachab, M. (2020). *Detection of Parkinson's disease from handwriting using deep learning: A comparative study*. Evolutionary Intelligence. <https://doi.org/10.1007/s12065-020-00456-0>
- Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the International Conference on Machine Learning* (pp. 6105–6114). <https://proceedings.mlr.press/v97/tan19a.html>
- Tolosa, E., Wenning, G., & Poewe, W. (2006). The diagnosis of Parkinson's disease. *The Lancet Neurology*, 5(1), 75–86. [https://doi.org/10.1016/S1474-4422\(05\)70285-4](https://doi.org/10.1016/S1474-4422(05)70285-4)
- Tong, Q., & Chen, L. (2021). Associations of Alzheimer's disease neuropathologic changes with clinical presentations of Parkinson's disease. *Journal of Alzheimer's Disease*, 81(1), 201–207. <https://doi.org/10.3233/JAD-210408>

- UCSF Memory and Aging Center. (n.d.). *Parkinson's disease dementia*. <https://memory.ucsf.edu/dementia/parkinsons/parkinson-disease-dementia>
- University of Rochester Medical Center. (n.d.). *Anatomy of the brain*. <https://www.urmc.rochester.edu/encyclopedia/content.aspx?ContentTypeID=85&ContentID=P00773>
- World Health Organization. (2023, March 15). *Dementia*. <https://www.who.int/news-room/fact-sheets/detail/dementia>
- Xie, A., Gao, J., Xu, L., & Meng, D. (2014). Shared mechanisms of neurodegeneration in Alzheimer's disease and Parkinson's disease. *BioMed Research International*, 2014. <https://doi.org/10.1155/2014/717419>
- Yücelbaş, C. (2021). A new approach: Information gain algorithm-based k-nearest neighbors hybrid diagnostic system for Parkinson's disease. *Physical and Engineering Sciences in Medicine*, 44(2), 511–524. <https://doi.org/10.1007/s13246-021-01001-4>
- Zegers, C., Posch, J., Traverso, A., Eekers, D., Postma, A., Backes, W., Dekker, A., & van Elmpt, W. (2021). Current applications of deep-learning in neuro-oncological MRI. *Physica Medica*, 83, 161–173. <https://doi.org/10.1016/j.ejmp.2021.03.007>
- Zesiewicz, T. A., Baker, M. J., Wahba, M., & Hauser, R. A. (2003). Autonomic nervous system dysfunction in Parkinson's disease. *Current Treatment Options in Neurology*, 5(2), 149–160. <https://doi.org/10.1007/s11940-003-0021-6>