Optimizing Parkinson's disease Classification in MRI Scans Using a Modified ResNet50 Architecture

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Abstract

The PD's (Parkinson's disease) is considered as the advanced neurodegenerative disorder which affects the movements as the dopamine producing neurons in the substantia nigra location present in the brain gets reduced. Since, the accurate basis of PD is the mixture of genetic and environmental factors, the PD results in the motor-related symptoms. However, the earlier detection is significant for the management of indications and slow growth, the diagnosis is difficult because of the identical with several neurodegenerative situations. The conventional techniques includes the clinical assessments, patients' profiles and the MRI, SPECT and PET scans. Since, the MRI's focus on the structural differences restricts the efficiency in the earlier phase of PD detection. Therefore, the ML and DL models are utilized in the classification of MRI scan images, as they face issues in the computations of features through several medical images and classification. Despite the enhancements, several difficulties such as restricted, labeled and noisy datasets. Hence, the study proposes a modified ResNet50 with CSAM (Channel Specific Attention Module) for the detection of PD in MRI scans with the utilization of PPMI and NTUA Parkinson's Disease dataset. In contrast to the existing models, the proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) achieves high performance and early detection. The proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) is evaluated using the performance metrics such as accuracy, precision, recall, and F1 score in which the proposed model obtains higher metrics values.

Keywords: Parkinson's disease, MRI scans, Deep Learning, PD Classification, Detection of Parkinson's disease

1. Introduction

The PD (Parkinson's disease) is recognized as the progressive neurodegenerative disease [1] which initially affects the movements of the individuals. It is caused due to the slower decrease in the dopamine generating neuron [2] which are present in the brain region of the substantia nigra [3]. The lack of dopamine in the PDs causes symptoms such as trembles, painfulness, instability postures and slower movements as the dopamine is the controller of motor. Also, the exact cause of PDs is not still known, it is considered as the combination of genetic and environmental parameters. Due to the growth of PDs, mood swings, perceptive failure and the automated dysfunction [4] happens. Hence, the earlier detection of PDs is significant in managing the symptoms and the development process. Moreover, the diagnosis of PDs is considered as complexity which gets associated to certain neurodegenerative infections with the reduction in biomarkers.

The conventional methods such as medical evaluations, patient's profiles along with the scans such as MRI (Magnetic Resonance Imaging) [5], SPECT (Single-Photon Emission Computed Tomography) [6] and PET (Positron Emission Tomography) [7]. The identification of PD is not possible in MRI as they focus on structural variations which are reserved in the earlier phase. The MRI scans has the capability of identifying the atrophy present inside the brain which are limited to PDs, since the MRI are utilized in medical assessments. Therefore, the ML (Machine Learning) and DL (Deep Learning) models are employed in the detection and classification of PDs from the MRI images. The ML models: SVM (Support Vector Machine) [8] is utilized in the classification of PDs for their ability in the effective management of high dimensional data, the RF (Random Forest) [9] is employed in the classification by collecting the outputs from different DTs (Decision Trees) which are developed on different extracted features. Additionally, the NBs (Naïve Bayes) [10] examines the features of MRI scan images for the classification of PD or non-PD whereas the KNN (K-Nearest Neighbours) [11] is employed for classifying and differentiating the image features with the frequent symptoms and reports. Due to the challenges faced by the ML models such as exhaustive computation of features which are not common for all the clinical images in the classification of PDs, the DL models are involved in the accurate classification of the MRI images.

Correspondingly, the DL models occupies the vital role in the medical domain by generating the accurate and efficient outcomes in the identification of PDs. It involves CNN (Convolutional Neural Networks) [12] which is recognised as the vital DL model in the detection of PDs using the MRI images. Due to the direct extraction of accurate features from the MRI images, the CNNs obtains high accuracy in differentiating the PD patients and non-diseased patients according to the spatial patterns. The pre-trained models such as ResNet, VGG and Inceptions are initially trained in larger datasets of images and fine-tuned for the detection of PDs in the MRI images. The LSTM and RNN [13] are utilized in the examination of data sequence. Additionally, the MRI images are employed in several sectors for the detection on the variations in the brain structure for processing the PDs which permits the earlier forecasting's. The hybrid CNN-LSTM [14] improves the flexibility and accuracy in the identification of PDs. This also reduces the difficulty of over fitting in the single model method. Despite the numerous innovations in the DL models and higher accuracy in the earlier detection [15] with the accurate treatment for PDs are larger. It faces several difficulties such as limited, labelled and noisy datasets with the latency in generalizability of the model and over fitting.

This study [16] highlights the potential of advanced network methods for detecting Parkinson's early. Researchers can expand on this by testing different network setups and ways to combine data, which could lead to better detection and earlier help for patients. This review [17] shows how useful machine learning can be for analysing facial expressions in Parkinson's. Future studies might create better computer programs that can pick up on small changes in emotion and movement. This could result in easy-to-use tools for diagnosing the disease. This review [18] points out the importance of computer-based methods for spotting and classifying Parkinson's. New research could look into innovative computer techniques and bring together different types of data to improve how accurately we diagnose the disease and tailor treatments.

This research [19] demonstrates that using specific features with deep learning, auto encoders, and neural networks works well to find Parkinson's. Scientists can explore new ways to pull out key features and use deep learning to improve detection and examine different types of data. This study [20] emphasizes how machine learning can help detect Parkinson's early and classify how severe it is. Future efforts can refine machine learning models to predict how the disease will progress and customize treatment, which will ultimately improve patient care.

The Accurate and timely diagnosis PD is challenging due to its complex nature, reliance on subjective clinical evaluations, and limitations of conventional imaging techniques like MRI in early stages. While ML and DL models show promise in PD detection from MRI images, they face difficulties like limited, labelled, and noisy datasets, as well as issues with generalizability and over fitting. This necessitates the development of more advanced and robust DL models to enhance early and accurate PD diagnosis, enabling timely intervention and improved patient outcomes.

Though numerous techniques are used for the detection of PDs from the MRI scan images, the proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) is utilized for the detection of PDs in the MRI scan images. The NTUA Parkinson's Disease and PPMI dataset are utilized in the proposed model. The proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) is compared with the existing models and is evaluated using the metrics such as accuracy, precision, recall and F1 score. When compared with the existing models, the proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) obtains better performance and the earlier detection.

1.1 Research Contribution

The proposed model employs the objectives such as:

- To validate the proposed model using the NTUA Parkinson's and PPMI dataset.
- To detect the PDs from the MRI scan images, the proposed model uses the Channel-Specific Attention Module (CSAM) in ResNet50.
- To evaluate the effectiveness of the proposed model by the performance metrics such as accuracy, precision, recall and F1score.

1.2 Paper Organization

The paper is divided into four sections. Section II comprises the prevailing models with diverse DL and ML algorithms. Section III illustrates the methodology of the entire study with their equivalent algorithms. Section IV

shows overall results and analysis of proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) and Section V comprises of the conclusion and the future work of proposed model.

2. Literature review

The ML and DL techniques are incorporates in the classification of PD for enhancing the diagnosis accuracy by examining the compound, higher dimensional data such as EEG and MRI scan images. They detects the subtle patterns occurring in the brain and its structure which has not been done by conventional techniques, by handling the multimodal data for the complete diagnosis. As the ML and DL techniques, can learn from the larger datasets and increases the earlier identification and predictions of PDs results in an exact and consistent diagnostic tackles. Correspondingly, the prevailing study [21] has tackled the issues of earlier detection of PD with the utilization of LightGBM and ML methods on ML techniques in the fused EEG and MRI data. The dataset has been processes utilizing the PCA (Principal Component Analysis) for the purpose of dimensionality reduction and has been evaluated using the 10-fold cross validation. As a result, average range of accuracy, sensitivity and specificity has been obtained in the classification of PD. Additionally, the study [22] has introduce the DL and radiomics techniques for the automation of PD diagnosis and has tackled the need of neutral diagnostic techniques. It has utilized the VB net for the automatic identification and segmentation of brain sub regions and the radiomics features are extracted from the particular areas. As a result, the SVM model which has been based on the combined features, has obtained better performance in the AUC, specificity, sensitivity and the metrics on both training and testing set.

As several prevailing studies has utilized the speech data with low accuracy and defective evaluation techniques, the study [23] has introduced the two stage diagnostic model with the utilization of a regularized linear SVM for the feature refinement and DNN for classification. The suggested model has obtained better range of accuracy under LOSO (Leave One Subject Out) and CV (Cross Validation) on K-fold CV for two diverse voice recordings in the target the datasets, and has outperformed the prevailing models. Alternatively, the study [24] has integrated the automated augmentation of MRI images utilizing the DCGAN (Deep Convolutional Generative Adversarial Networks), feature extraction and the classification has been performed utilizing the pre-trained models such as VGG16, Xception and the InceptionV3. The suggested hybrid /inceptionV3 with the QSVM (Quantum SVM) has obtained the prediction accuracy of 87.5%, precision of 95%, recall as 84% and F1 score as 89%.

Similarly, the existing study [25] has utilized the co-learning technique for the multimodal fusion of imaging and medical data obtained from the PPMI dataset. The DenseNet along with the EN (Excitation Network) has outperformed the other models and the XAI models which has highlighted the main brain areas such as right temporal and left pre-frontal areas and the lateral ventricles which has been considered as the earlier PD bio-markers. Additionally, the study [26] has suggested the cliff-PD model for the detection of PD with the utilization of Clifford gradient RNN classifier with the MRI and EEG signals which has highlighted the significance of earlier diagnosis of disease. The MRI images has been denoised utilizing the MSR (Multi-Scale Retinax) and the EEG signals which has been denoised utilizing the SWT (Stationery Wavelet Transform) filter. The suggested model has been utilized for the classification of MRI images and the EEG signals and has obtained better range of accuracy in contrast to the SVMs, Alex Net and the CROWD auto-encoder. The study [27] has utilized the multi-modal neuroimaging data for the classification of PD which has been trained on larger dataset which consists of T1-weighted and the diffusion-tensor MRI data which has been collected from 1264 individuals. The suggested CNN model has obtained accuracy as 80.8%, ROC-AUC as 0.89, specificity as 82.4% and 79.1% as sensitivity on the test set and has also utilized the smooth grad saliency maps for the enhancement of explainable decision-making procedures.

Simultaneously, the study [28] has introduced the enhanced image allocations method utilizing the affine transformation which has permitted the rotations from 0 – 135 degrees which has been significant in the enhancement of accuracy in diagnosis. Additionally, the U-net model has been utilized for the detailed segmentation of image with the isolation of affected brain areas along with the DenseNet for the classification of PD. The hybrid model has outperformed the prevailing models with the better range of metrics value. It has involved the user- friendly graphical interface for the effective and accurate detection of PD in the MRI scans images. Alternatively, the study [29] has introduced the hybrid radiomics with the SVM for the automatic detection of earlier stage of PD with the utilization of Neuro melanin-sensitive MRI. The hybrid SVM has obtained 96.3% of accuracy in test set and 95.8% in validation test and has outperformed the radiomics features with the saliency map for classification. Similarly, the study [30] has introduced the ML model for contrasting the PD from the MSA (Multiple System Atrophy) utilizing the multimodal PET/MRI radiomics and the medical features. It

has involved 119 patients who has took brain CT and MRI for obtaining the metabolic and structural images. The models has obtained average range of AUC in the training set.

Subsequently, the study [31] has utilized the dataset with 7500 MRI images and the 12 medical evaluations records from the PPMI database for the efficient maintenance of imbalanced data. As a result, the suggested model has obtained 98.44% of recall with the additional tree classifier and accuracy of 85.08% in the detection of PD with the utilization of CNN architectures such as DenseNet169. Additionally, the prevailing study [32] has utilized sic DL models such as VGG16, VGG19, ResNet18, ResNet50, ResNet101 and Vit on the NIATS dataset and has tackled the challenges in the detection of PD utilizing the handwriting's. As a result, the VGG19 model in addition with the cosine annealing scheduler has obtained 96.67% of accuracy. Consequently, the existing study [33] has utilized the fNIRS (functional near Infrared Spectroscopy) data for the extraction of 792 temporal and spatial features extracted from 120 PD affected patients which has been classified utilizing the logistic regression model. As a result, average accuracy has been obtained along with the recall, F1 score and AUC of 1 with the utilization of 14 features.

On the other word, the study [34] has employed the network which has been trained on medical images for the diagnosis of PD utilizing the SPECT images. The dataset which has been comprised of 1213 SPECT images with 1000 PD and 213 Non-PD images which has been classified into 70% training, 10% validation and 20% of testing data. As a result, the retrained PARNet which has been based on COVID19 ResNet model, it has obtained 95.43 % of accuracy with the average range of sensitivity, specificity, precision and recall. In a similar vein, the prevailing study [35] has utilized the KNN and FNN models with the utilization of dataset with 195 voice capturing from 31 patients due to the intersection with the other symptoms. As a result, the FNN model has obtained better level of metrics values whereas the KSVM model has obtained 95.89% of accuracy, 96.88% of recall, 98.71% of precision and 97.62% of F1 score. Additionally, the study [36] has employed the DenseNet201 and VGG16 for observing the PDs spiral drawings public dataset, and tackle the problems of detection using drawings by handwritten. As a result of utilizing 204 spiral and the wave drawings of PD, the suggested model has obtained 90% accuracy.

Additionally, the study [37] has utilized the CNN, BGWO and SVM for feature extraction and feature selection which has tackled the issues faced in the earlier diagnosis in PDs. As a result of evaluating the model on the new hand PD dataset, better range of accuracy has been obtained. Consequently, the prevailing study [38] has utilized the CNN algorithm with VGG16, ResNet50, EfficientNetB0 and the EfficientNetB1 for enhancing the accuracy in the diagnosis of PDs. As a result of evaluating the model on the PPMI (Parkinson Progression Markers Initiative) dataset, better range of accuracy has been obtained in the classification of PD and non PD patients utilizing distinct activation functions. The existing study [39] as recommended the MvRNA concerning ResNet18 with BWH (Basic Block with Hybrid Dilated Convolution). As a result, segmenting the model on MRI data, suggested model has obtained 81.84% of accuracy in contrasting the healthier and PD patients by evaluating on the PPMI dataset.

2.1 Problem identification

The following gaps has been identified by the above existing studies:

- The study's dependence on PPMI database has restricted the generalizability due to the potential demographic biases and un-representation of several groups which has influenced the application of model in real time medical sectors.
- The study has restricted over-reliance on explicit performance metrics such as accuracy, which has not completely represented the class inequities in dataset which has resulted in wrong outcomes specifically the false negatives.
- The hybrid model is challenging for interpretation, with the reduction of medical applicability in which the elaboration is considered to be crucial.

3. Research methodology

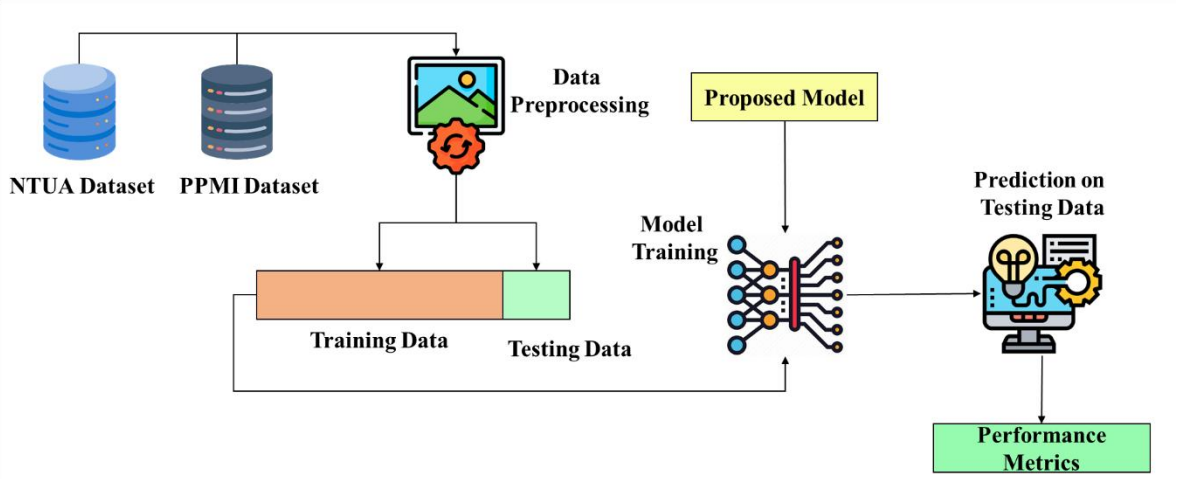

Figure.1 Overall Flow

Figure.1 depicts the overall flow of the proposed model in which the process is initiated with the utilization of two datasets namely the NTUA Parkinson's image dataset and PPMI (Parkinson's Progression Markers Initiative) dataset. The dataset is directed to the data pre-processing phase where the data is divided into two categories for training of 80% and testing of 20%. The testing of data is performed for evaluating the performance of the proposed model. Further, the model is trained utilizing the training data for refining the parameters depending upon the data. Next to the training, the trained model is tested on the test data for providing the predictions. As a continuation, the predictions are examined utilizing the performance metrics for assessing the efficiency of the proposed model.

3.1 Dataset description

The proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM) utilizes two datasets namely the NTUA Parkinson's image and PPMI dataset.

NTUA Parkinson's Image Dataset

Data is collected from the github website. The link of the dataset is given below for reference. https://github.com/ails-lab/ntua-parkinson-dataset . The dataset presently comprises MRI examinations and DaT scans from 78 individuals, 55 suffering from PDs, whereas 23 serves as normal control subjects. It involves sensors related to measurements, such as the gyroscope and accelerometer which is gathered from the Parkinson diseased patients which are utilized for the development on the study of disease and to introduce the ML which aids in earlier detection and symptoms evaluation.

PPMI Dataset

The PPMI dataset aims to the identification of biomarkers in PD development. It involves the data from PD and non-PD patients with the medical, Neuro-imaging, genomic and biomarker data gathered before. It focuses on the earlier diagnosis, tracking the disease growth and assessment of therapeutic interferences. The data is gathered per annum and covers a larger range of variables such as motor and cognitive evaluations. Moreover, the researchers utilizes the PPMI for the identification of disease markers, examine genetic factors and the growth of diagnosis equipment's and therapies for PD. The PPMI dataset link is given below: https://www.ppmi-info.org/

3.2 Data pre-processing

The data-pre-processing assists in eradicating the unnecessary and noisy data in the dataset. The two steps of pre-processing includes image resizing and data normalization.

Image resizing

It guarantees that the images present in the dataset has reliable dimensions, in assisting the model training. It inhibits the issues regarding the computation and permits the model for acquiring similar patterns through diverse samples. The enlarging commonly utilizes the interpolation methods for evaluating newer pixels, whereas the shrinking eliminates the pixels by missing the details.

Data Normalization

The normalization modifies the values of pixels for having a mean of 0 and SD (Standard Deviation) of 1 and 1 or -1 by enhancing the stability of the model in the training process with a constant standardized range, assisting for convergence. It also eliminates the features of larger values from directing with the ML techniques and enhances the performance of the model and flexibility of the training set. The communal techniques involves minmax scaling and the z-score.

3.3 Proposed Modified ResNet50 with Channel-Specific Attention Module (CSAM)

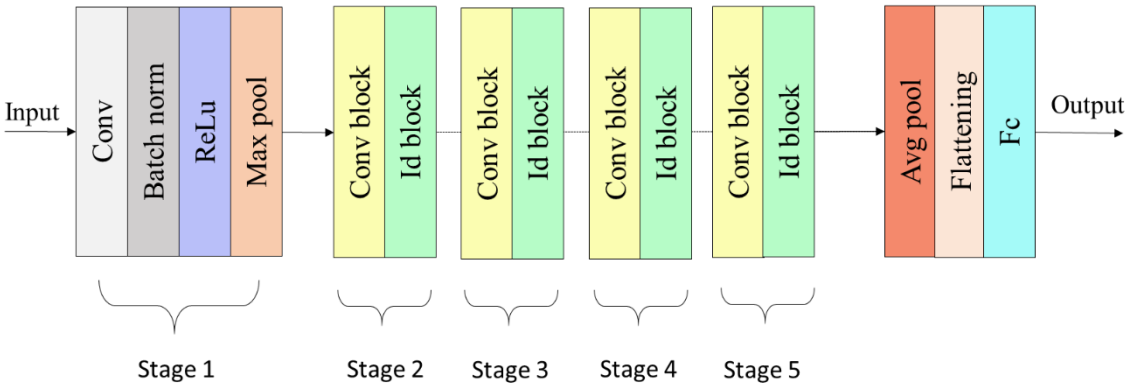

Figure.2 ResNet50 Architecture

Figure.2 deliberates the architecture of ResNet50 which is initiated with the input data processed in the Conv (Convolutional) layer. It is followed by the batch normalization which aids in alleviating the leaning process by the normalization of outcomes obtained from the convolutional layer. Further, the data is passed on through the activation function ReLu, which presents the non – linearity to the model by permitting additional difficult patterns. As a continuation, the data is passed to the max pooling layer where the spatial dimensions present in the data are reduced by holding the significant features with the decrease in the difficulties of computing. The above process happens in stage-1. In addition with, the stage-2 consists of the convolutional block and the identity block which happens in continuous stages in which each of the stage consists of the convolutional block and identity block which permits for the deep feature extraction. The final stage involves the average pooling layer which decreases the dimensionality and then data is flattened to a 1D vector. The flattened outcome is passed to a FC (Fully Connected) layer which generates the final predictions.

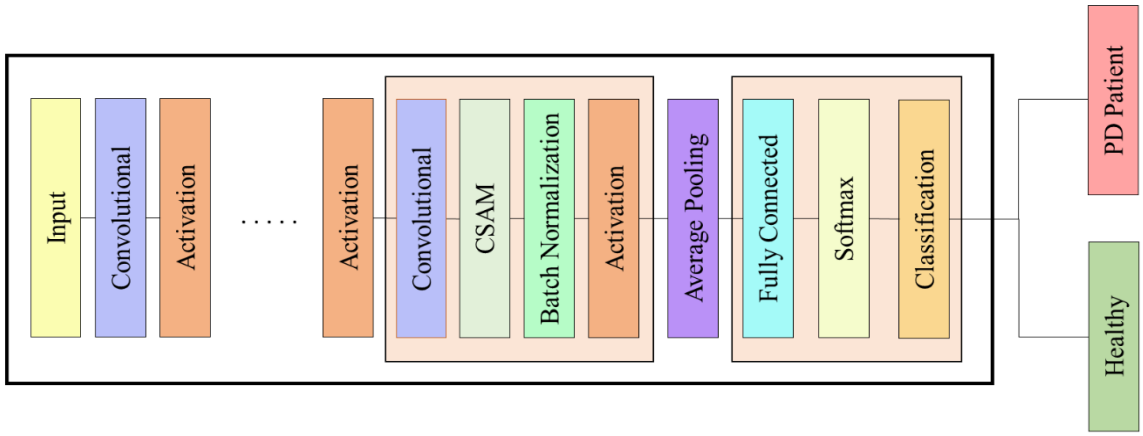

Figure.3 Modified ResNet50 with Channel-Specific Attention Module (CSAM) Architecture

Figure.3 illustrates the architecture of proposed modified ResNet50 with CSAM (Channel Specific Attention Module) which classifies the MRI images as PD or non-PD patients. The model is initiated with the input layer which process the raw data along with the convolutional and activation layers for extracting and increasing the data features. The inclusion of CSAM (Channel-Specific Attention Module) after the convolutional layer and batch normalization has enhanced the capability of the model in focussing the appropriate spatial and channel wise features in the enhancement of performance on the difficult strategies such as classification. The CSAM enhances the feature extraction with the significant channels and spatial parts present in the feature map. The channel attention regulates the significance of various channels with the use of global pooling and the convolutional layers for computing the attention weights. The spatial attention stresses the important regions with the integration of pooling among the channels with the pooled features by providing the spatial attention weights through convolution. Further, the activation functions are integrated and the data is passed on to the average pooling layer for the reduction of dimensionalities. The output is passed on to the fully connected layer for incorporating the features which is followed by the softmax layer for the classification. Finally, the output layer classifies the input data to two parts such as PD and Healthy. The CSAM module along with the attention mechanism permits the model for aligning the significant features and eliminates the unrelated, by making the proposed model effective and accurate in contrasting the two classes. The CSAM in the proposed model is a vital innovation for enhancing the capability of classification in the model.

4. Results and Discussion

This section includes the experimental results of proposed modified ResNet50 with CSAM (Channel Specific Attention Module) with performance metrics, EDA (Exploratory Data Analysis), performance analysis and comparative analysis.

4.1 Performance metrics

4.1.1 Accuracy

The accuracy of the proposed model is calculated by

$$\text{Accuracy} = \frac{(Tr\_P+Tr\_N)}{(Tr\_P+Tr\_N+Fl\_P+Fl\_N)}$$

Where Tr_P signifies true positive rates, Tr_N signifies the true negative rates, Fl_P signifies the false positive rates and Fl_N signifies false negative rates.

4.1.2 Precision

It is utilized for the purpose of saving the information and is equated using,

$$\text{Precision} = \frac{Tr\_P}{(Tr\_P+Fl\_P)}$$

4.1.3 Recall

It is utilized in the detection of the total number of true and false incidents of the positive instances.

$$\text{Recall} = \frac{Tr\_P}{(Tr\_P+Fl\_N)}$$

4.1.4 F1-Score

The harmonic mean value of recall and precision is measured using F1 score.

$$\text{F1 score} = 2 * \frac{R \times P}{R+P}$$

Where P and R is denoted as precision and recall.

4.2 EDA (Exploratory Data Analysis)

This section comprises of the graphical representations of the proposed modified ResNet50 with Channel-Specific Attention Module (CSAM) on NTUA and PPMI datasets.

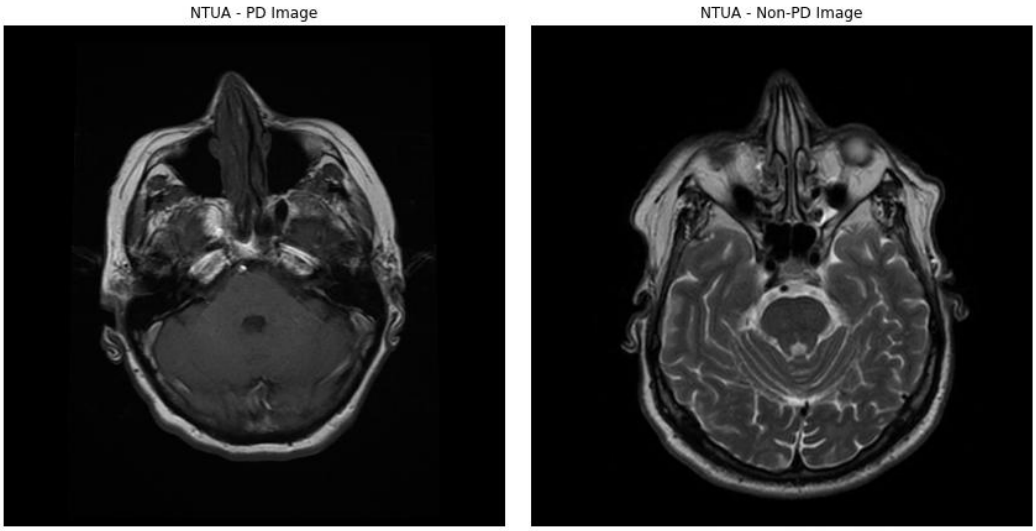

Figure.4 PD and Non PD images – NTUA Dataset

Figure.4 depicts the MRI scans on brain using the NTUA dataset. The PD image present on the left side demonstrates the abnormalities resulting in the neurological situation, whereas the Non-PD image on the right side demonstrates the normal brain.

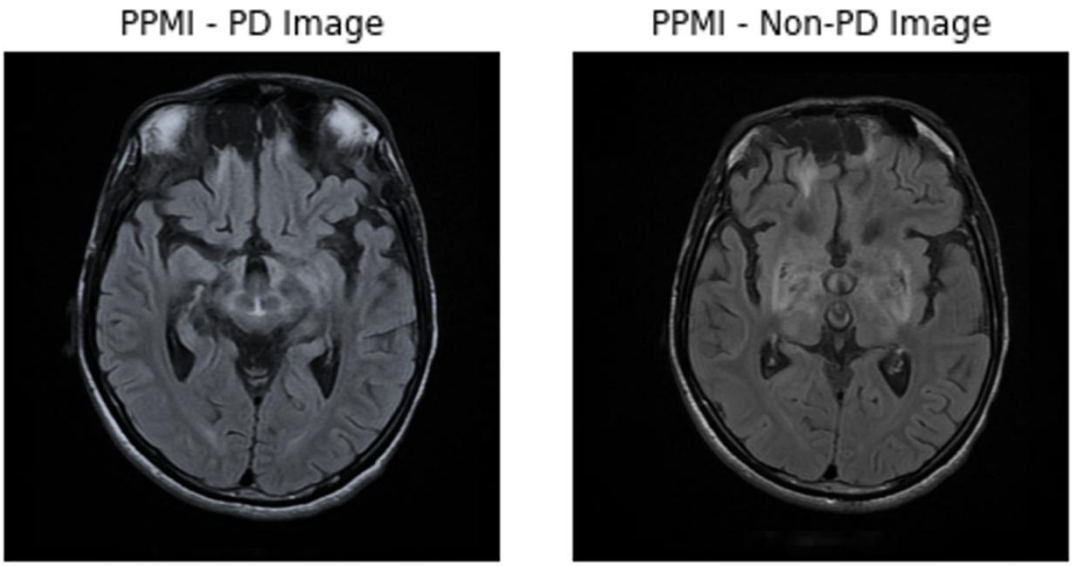

Figure.5 PD and Non PD images – PPMI Dataset

Figure.5 depicts the MRI scans on brain using the PPMI dataset. The PD image present on the left side demonstrates the abnormalities resulting in the neurological situation, whereas the Non-PD image on the right side demonstrates the normal brain.

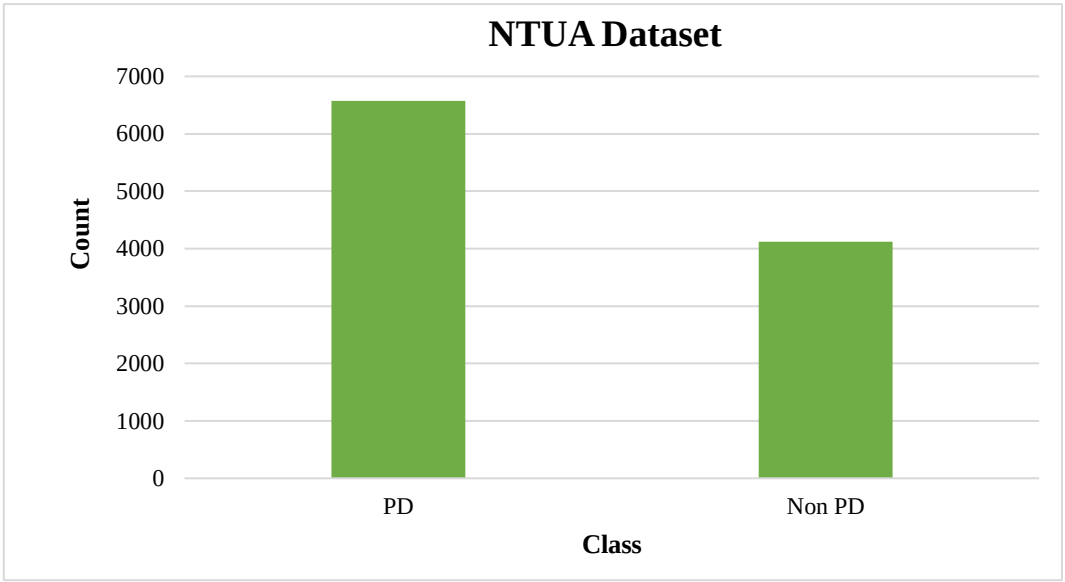

Figure.6 Class Distribution – NTUA Dataset

Figure.6 depicts the class distribution of PD and non- PD images on NTUA dataset where there are 6574 PD images and 4116 non-PD images.

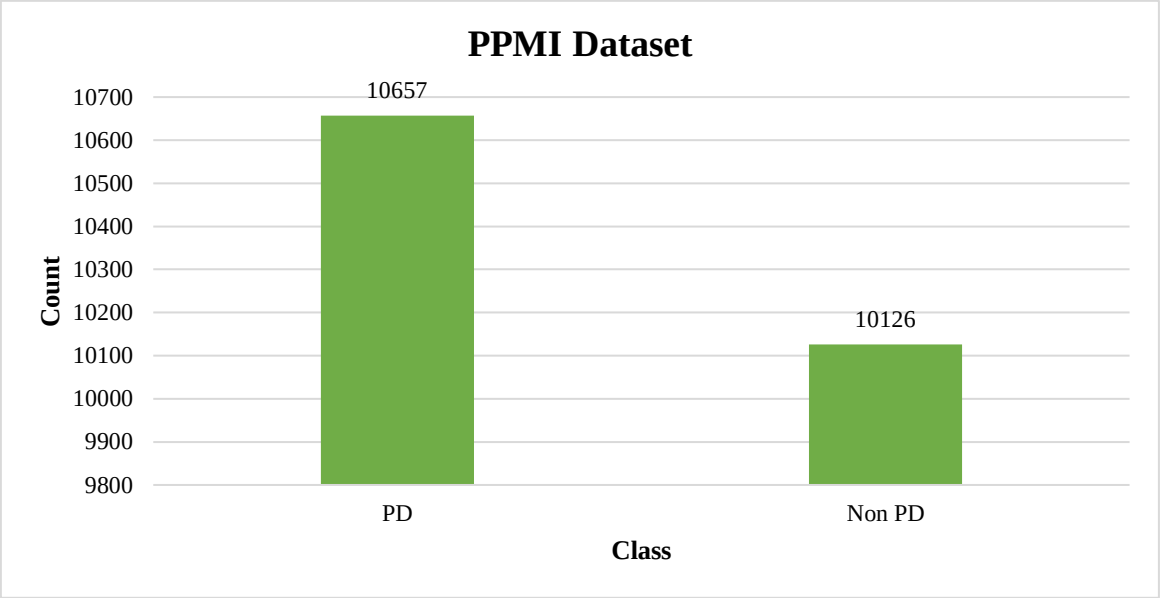

Figure.7 Class Distribution – PPMI Dataset

Figure.7 depicts the class distribution of PD and non- PD images on PPMI dataset where there are 10657 PD images and 10126 non-PD images.

4.3 Performance analysis

The below section consists of performance analysis of the proposed modified ResNet50 with Channel-Specific Attention Module (CSAM) on NTUA and PPMI datasets by confusion matrix's ,model loss and accuracy on NTUA and PPMI datasets.

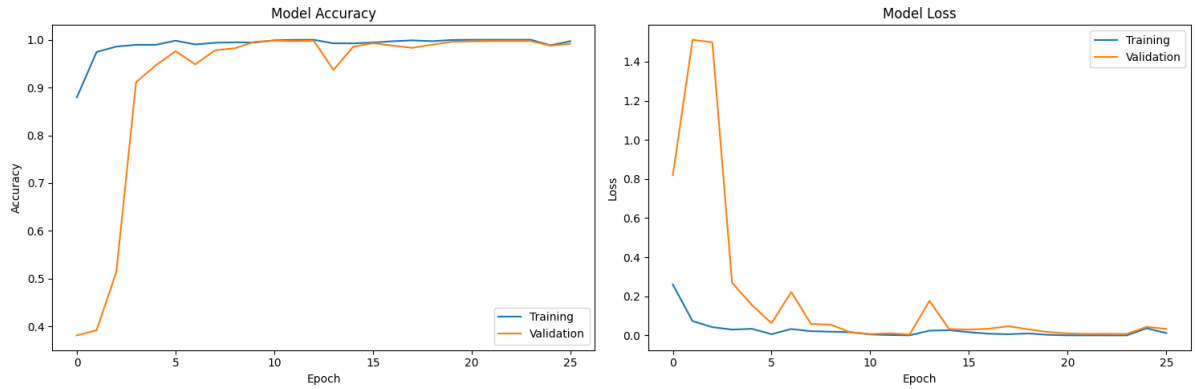

Figure.8 NTUA Training Metrics

Figure.8 depicts the training and validation curves. The model accuracy demonstrates the training accuracy reaching the better levels with the epoch of 3, whereas the validation accuracy gets reduced towards the plateau. The model loss demonstrates the high reduction in training and validation which is followed by the variations before they are alleviated near to the 0.

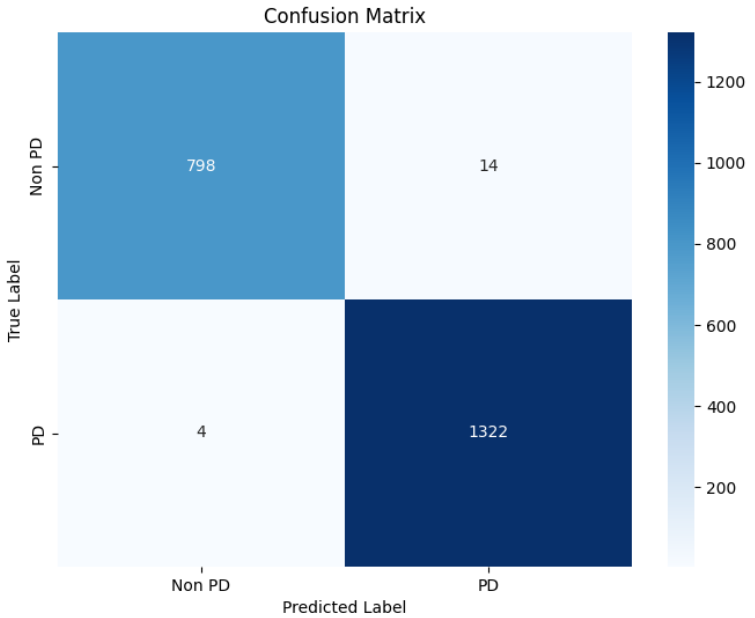

Figure.9 Confusion Matrix – NTUA Dataset

Figure.9 depicts the confusion matrix of the classification of PD and non PD images on NTUA dataset, the model has correctly detected 798 Non PD images and 1322 PD images with 14 FPs (False Positives) which is actually Non PD but predicted as PD along with 4 FNs (False Negatives) which are PD but predicted as Non PD. The proposed model has demonstrated high accuracy with the larger number of true labels.

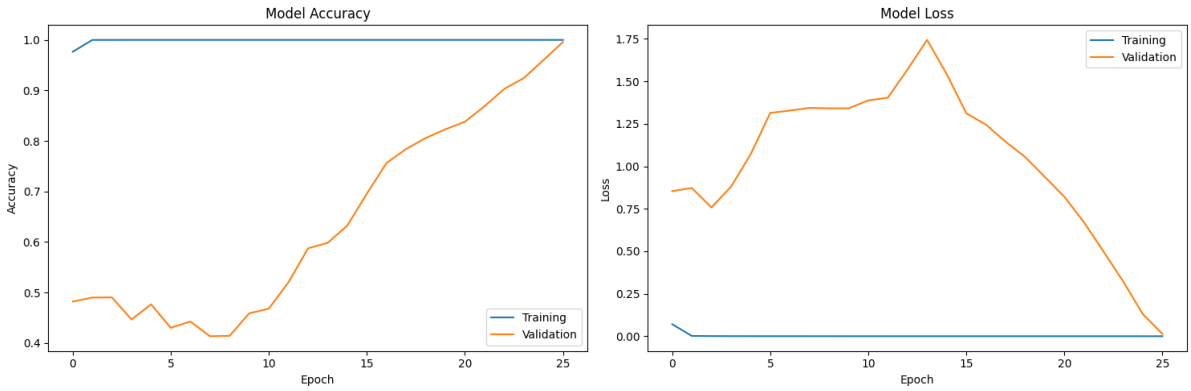

Figure.10 PPMI Training Metrics

Figure.10 depicts the model accuracy graph which displays the training accuracy which plateaus at 1.0 next to the first few epochs, whereas the validation accuracy rises from around 0.4 to about 0.98 over 25 epochs. The model loss graph specifies that the training loss quickly drops to near 0 and remains. On the other hand, the validation loss varies, climaxing at approximately 1.75 around epoch 13 before decreasing to approximately 0.05 by epoch. A lower loss commonly designates a better model, with the caution that the model may be overfitting if the loss is too low.

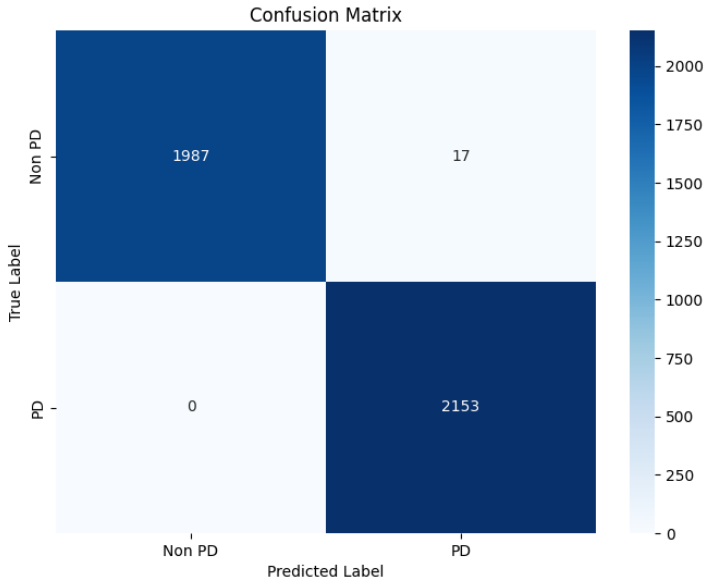

Figure.11 Confusion Matrix – PPMI Dataset

Figure.11 depicts the confusion matrix of the classification of PD and non PD images on PPMI dataset, the model has correctly detected 1987 Non PD images and 2153 PD images with 17 FPs (False Positives) which is actually Non PD but predicted as PD along with 0 FNs (False Negatives) which are PD but predicted as Non PD. The proposed model has demonstrated high accuracy with the larger number of true labels.

4.4 Comparative analysis

This section deliberates the accuracy comparison of the proposed modified ResNet50 with Channel-Specific Attention Module (CSAM) with the existing models on the NTUA and PPMI datasets and the graphical representation.

Table.1 Comparative analysis of proposed model with existing models – NTUA Dataset [40]

Model	Accuracy
DenseNet121	90.70
MobileNet V3	96.53
Optimized MobileNet V3	98.36
Proposed	**99.16**

Table.1 depicts the comparison of the proposed model with the existing models on NTUA dataset in which the proposed model has obtained 99.16% of accuracy whereas the existing models has obtained average range of accuracy where the DenseNet121 as 90.70%, MobileNetV3 as 96.53%, Optimized MobileNetV3 as 98.36% respectively.

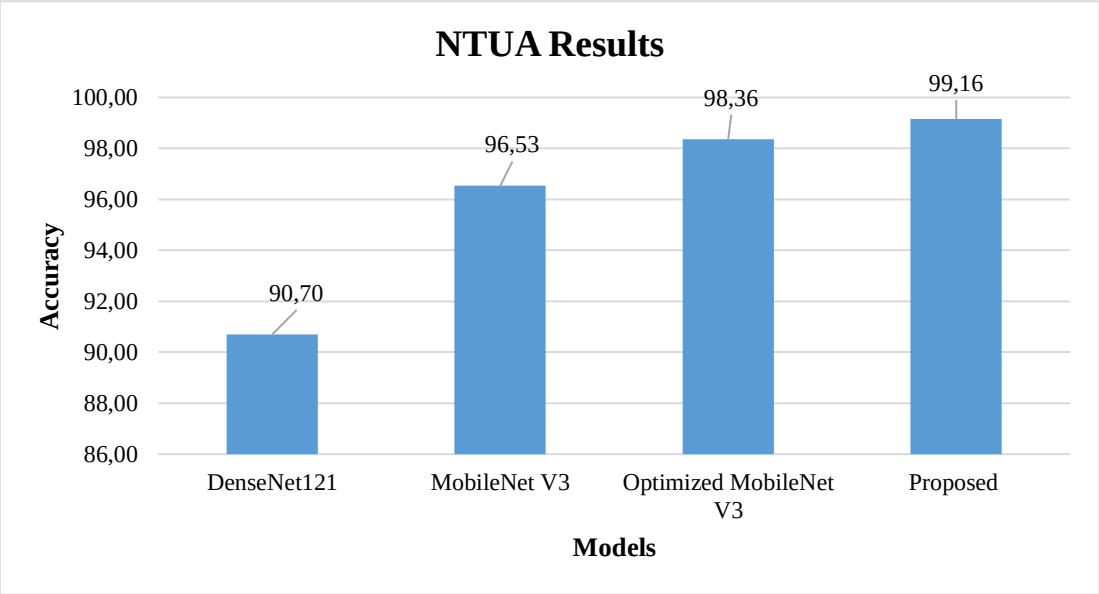

Figure.12 Comparative analysis of proposed model with existing models – NTUA Dataset

Figure.12 depicts the graphical representation on the comparison of the proposed model with the existing models on NTUA dataset in which the proposed model has obtained 99.16% of accuracy whereas the existing models has obtained average range of accuracy where the DenseNet121 as 90.70%, MobileNetV3 as 96.53%, Optimized MobileNetV3 as 98.36% respectively.

Table.2 Comparative analysis of proposed model with existing models – PPMI Dataset [41, 42]

Model	Accuracy (%)
3D CNN model	88.90
LeNet-based	95.00
AlexNet-based	95.00
MobileNet V3	98.09
Optimized MobileNet V3	99.13
Proposed	**99.28**

Table.2 depicts the comparison of the proposed model with the existing models on PPMI dataset in which the proposed model has obtained 99.28% of accuracy whereas the existing models has obtained average range of accuracy where the 3D CNN model as 88.90%, LeNet based as 95.00%, Alex Net-bases as 95.00%, MobileNetV3 as 98.00%, Optimized MobileNetV3 as 99.13% respectively.

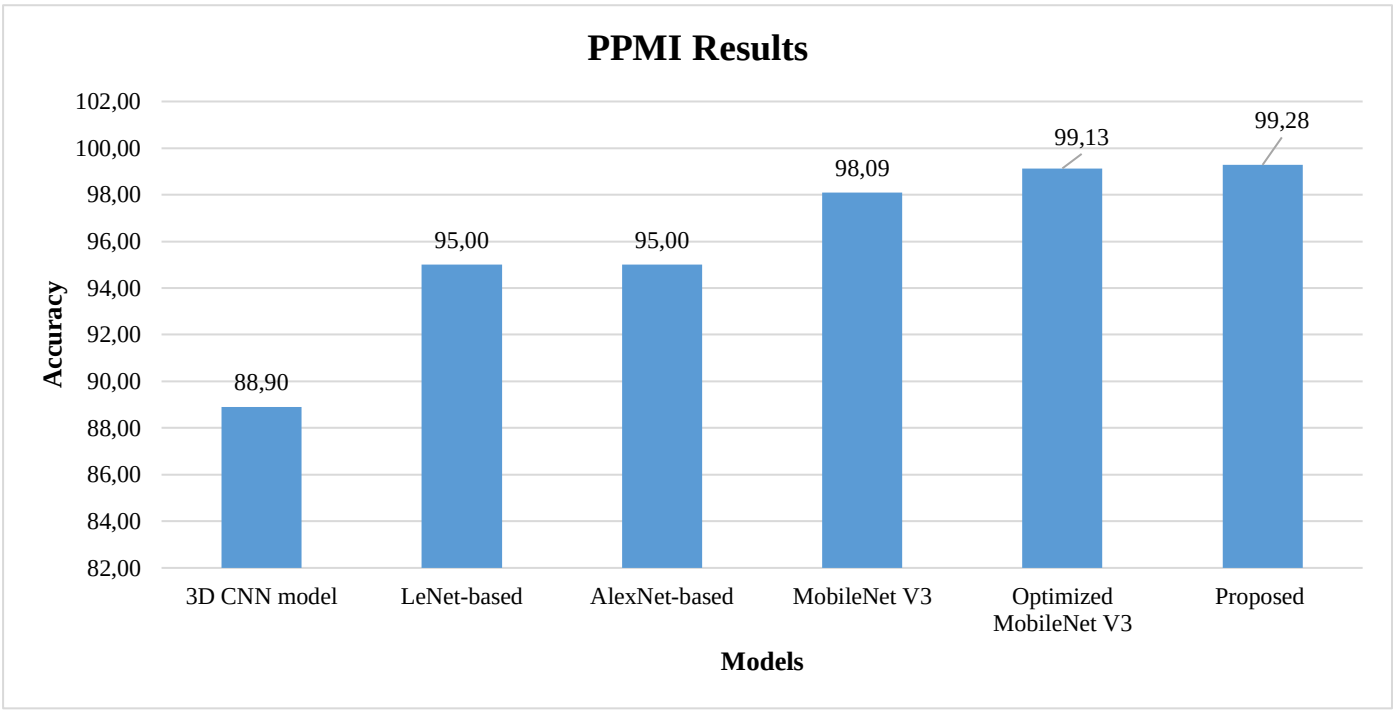

Figure.13 Comparative analysis of proposed model with existing models – PPMI Dataset

Figure.13 depicts the graphical representation on the comparison of the proposed model with the existing models on PPMI dataset in which the proposed model has obtained 99.28% of accuracy whereas the existing models has obtained average range of accuracy where the 3D CNN model as 88.90, LeNet based as 95.00, Alex Net-bases as 95.00, MobileNetV3 as 98.00, Optimized MobileNetV3 as 99.13 respectively.

5. Conclusion and Future recommendations

The PD is considered as a communal neurological disorder which affects the movement. The symptoms of PDs includes stiffness, tremors, and issues with balance and coordination. As the detection of PDs using MRI images is a major challenges, several conventional methods has been utilized in the diagnosis of PDs. The conventional techniques has faced numerous challenges such as higher inter-subject variations in the symptoms and progression of PD , the shortage and class inequality in the datasets, relationships between clinical manifestations has obstructed the growth of strong and generalizable model for the accurate detection of PD. Hence, to tackle the challenges faced by the existing studies, the proposed research has utilized the Modified ResNet50 model with a Channel-Specific Attention Module (CSAM) for the detection of PD. The proposed model has been evaluated and trained using the NTUA Parkinson's and PPMI dataset. The proposed Modified ResNet50 model with a Channel-Specific Attention Module (CSAM) for the detection of PD is the modifications made in the layers of ResNet50 which has enhanced the performance of the detection and classification as PD and non PD patients using MRI images. The proposed model has been evaluated with performance metrics such as accuracy, recall, precision and F1 score in which the proposed model has achieved superior values in accuracy of 99.16% on NTUA Parkinson's Disease dataset and 99.28% of accuracy in PPMI dataset which has outperformed the existing models in the classification as PD and non PD patients. However, the proposed research has obtained ideal performance .The future work of the proposed research will utilize advanced DL algorithms in the detection of PDs.

Declarations

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Conflict of Interest

There is no conflict of interest.

Data Availability Statement

There is no research data outside the submitted manuscript file.

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