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NOVE-Seg: An Effective Framework for Detection of Alzheimer Disease Using Opti-FRCNN on Brain MRI

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ABSTRACT

Alzheimer Disease (AD) has been diagnosed using different Machine Learning (ML) or Deep Learning (DL) methods or by utilizing MMSE - Mini-Mental State Examination and physical tests in the medical field. Moreover, the development of medical imaging techniques creates a positive and significant impact in identifying functional and structural variations occurring in the brain, especially in neuroimaging. However, most of the time, due to inaccuracy or low-quality images, medical experts cannot predict the AD level, which leads to increased death cases. In the current research, an enhanced Fast RCNN - Region-based Convolutional Neural Network using the Bayesian Optimization method for the Image Segmentation process has been developed with the CNN methods that resolve the image classification issues with the proper variants such as VGG16 to acquire state-of-the-art performance. The Faster R-CNN with Bayesian optimization technique has been compared in terms of certain performance metrics such as accuracy, precision, recall, F1-score, and MAP - Mean Average Precision with the existing methods such as SVM - Support Vector Machine and MobileNetV2. Eventually, the proposed system procured efficient results compared to the other existing methods. In the future, large real-time datasets will be used with the integration of the proposed system to enhance accuracy and sensitivity.

1. INTRODUCTION

Magnetic resonance imaging - MRI has been utilized to evaluate the brain's anatomical structures because of its spatial resolution and ability to distinguish soft tissue. Generally, MRI is associated with limited health risk factors compared with other modalities such as PET-positron emission tomography and CT - computed tomography. Recently, tremendous progress has been made in evaluating brain injuries and examining brain anatomy with MRI. Therefore, disorders include multiple sclerosis and AD is related to the brain, and these diseases can be identified utilizing MRI. Tissue atrophy is one of the famous indicators for diagnosing AD [1, 2].

Furthermore, the brain MRI segmentation has been processed at different periods and utilized to evaluate structural variations in the brain. Certainly, it is significant to determine and classify the unhealthy tissue accurately, and these healthy structures are considered a significant process in Alzheimer diseases diagnosis [3]. However, it is complex to identify AD; CN - Cognitive Normal and MCI - Mild Cognitive Impairment have been considered challenging tasks in the past few decades.

AD is diagnosed utilizing MMSE - Mini-Mental State Examination and physical tests in the medical field. Furthermore, the development of medical imaging methods creates considerable impact on neuroimaging, and it plays a significant part in diagnosing functional and structural variations occurring in the brain, comprehending SPECT - Single Photon Emission Computed Tomography, FMRI - Functional Magnetic Resonance Imaging, PET - Positron Emission Tomography, and CT - Computer Tomography. MRI - Magnetic Resonance Imaging is utilized to examine structural variations generated because CN - Cognitive Normal and MCI - Mild Cognitive Impairments are considered challenging tasks [4].

Moreover, the advancement in computing methods and an unprecedented enhancement in DL-based models [5] are developed to manage and identify a neurological disorder such as AD [6]. Therefore, it is an irreversible, progressive, and chronic neurodegenerative disease that is medically exhibited by gradual loss, amnesia, and cognitive dysfunction of other functions. The prevalence of AD is projected to significantly rise to 152 million by 2050, leading to substantial societal, medical, and economic challenges. Despite ongoing research efforts, the underlying pathogenesis of AD remains incompletely understood, and effective therapeutic interventions to halt disease progression are currently lacking in the medical field. Nonetheless, early identification of AD, through Mild Cognitive Impairment (MCI) screening, is crucial for effective disease management, facilitating the search for suitable pharmaceutical interventions and preventive measures to mitigate its impact [7].

AD poses a significant and growing challenge to global healthcare systems, with its prevalence expected to rise dramatically in the coming decades. Early and accurate diagnosis of AD is crucial for effective management and intervention, yet current diagnostic methods are fraught with limitations. This paper addresses the pressing need for improved diagnostic techniques by proposing a novel framework, NOVE-Seg, which leverages Opti-FRCNN on Brain MRI data for the detection of AD.

Despite advancements in medical imaging technology, the diagnosis of AD remains largely reliant on clinical evaluation coupled with neuropsychological testing. While these methods can provide valuable insights, they are subjective, time-consuming, and often lack the sensitivity required for early detection. Additionally, the reliance on structural MRI scans for AD diagnosis presents challenges due to the subtle and heterogeneous nature of the disease-related changes in brain morphology.

The specific research gap this paper aims to address lies in the inadequacies of current diagnostic methods, particularly their inability to accurately detect early-stage AD and distinguish it from normal aging or other neurodegenerative disorders. Furthermore, existing approaches often struggle with the segmentation of relevant brain regions and the precise localization of pathological features indicative of AD.

In response to these challenges, the NOVE-Seg framework introduces a novel approach that integrates Opti-FRCNN, a state-of-the-art object detection model, with advanced segmentation techniques tailored for AD detection on Brain MRI scans. By harnessing the power of DL and optimizing feature extraction, NOVE-Seg aims to enhance the sensitivity, specificity, and efficiency of AD diagnosis, ultimately improving patient outcomes and facilitating timely interventions.

Physicians are utilizing various clinical methods to enable the classification of AD [8, 9]. Normally, it is represented that CSF - cerebrospinal fluid concentration has been clinical deal with certain diseases such as AD. The increase in norepinephrine levels in the CSF defines the Disease's signs of progress. The CSF is accumulated utilizing a ventricular puncture, and the CSF will be gathered from the ventricles of the brain. This laborious procedure will create the possibility of bleeding risk in the brain; hence, medical imaging methods such as neuroimaging play a significant part in finding the functional and structural variations that occur in the brain. Furthermore, the MRI concept is utilized to manage the structural variations caused due to AD manifestation. Neuroimaging methods are used widely in the medical field to visualize the anatomical variations in the brain [10].

Furthermore, different AD stages are analyzed in the clinical field, including early stage, pre-dementia, middle, and advanced stage. The main symptom to be noticed in the predementia stage is the normal aging process. The early stage includes executive function, memory, and learning impairment resulting from complex language. The middle stage symptoms including speech difficulties, especially in writing and reading are attenuated. The advanced stage is the final stage where Alzheimer patients may express apathy. It is difficult for patient to do simple tasks independently, resulting in bedridden and death ensues [11]. Therefore, the AD prediction is completely based on the previous illness history and the existence of psychological and neurological features. These medical records are obtained from the behaviour observed by the patients. Based on the patterns and illness level, supplements or medicines are taken into consideration in the AD screening process and advanced imaging techniques such as PET-CT - Positron Emission Tomography-Computed Tomography, MRI - Magnetic Resonance Imaging [12], and CT - Computed Tomography methods.

Tremendous progress has been carried out in the image processing field because of the availability of a large dataset that yields accurate model learning. The most popular datasets used in the research are ImageNet, that consist of 1.2 million images with a thousand of distinctive classes. On the other hand, transfer learning has also been used in these trained networks within smaller datasets with connected layers [13].

Scalable framework:

The NOVE-Seg architecture for AD identification utilising Brain MRI shows encouraging findings, but its scalability to bigger datasets and different patient groups is limited. For large-scale investigations and real-world clinical applications, future research should optimise the framework's computing efficiency and scalability to ensure robust performance across imaging centres and acquisition techniques.

Performance on heterogeneous data:

This study tests the NOVE-Seg framework on curated datasets with similar imaging and illness patterns. To determine its generalizability and robustness in real-world clinical contexts, the system should be tested on additional heterogeneous datasets with different imaging characteristics, scanner models, and patient demographics.

Required external validation:

The NOVE-Seg framework shows encouraging results in internal validation tests, but external validation on independent datasets is needed to ensure its generalizability and dependability across demographics and clinical situations. Further research should focus on multi-center studies and clinical consortia to gather diverse and representative datasets for thorough external validation of the framework's performance.

Clinical interpretability and explainability:

In clinical practice, the NOVE-Seg framework's predictions may be difficult to grasp and explain despite its high AD detection accuracy. The framework's segmentation and classification results should be interpreted and therapeutically useful in future research to improve healthcare practitioners' use of it.

Brain MRI data reveal AD structural:

abnormalities, but adding functional MRI (fMRI), PET, and CSF biomarkers could improve diagnostic accuracy and predictive performance. Multi-modal data fusion and integration within the NOVE-Seg architecture should be studied to improve AD detection and characterisation.

Exploring advanced DL structures:

Opti-FRCNN detects AD well, however attention mechanisms, graph neural networks, and self-supervised learning may improve its performance and robustness. To improve AD detection accuracy and clinical value, these new approaches should be tested in the NOVE-Seg framework. while the NOVE-Seg framework shows promise in AD detection using Brain MRI, addressing the identified limitations and exploring future research directions are crucial for advancing its clinical applicability, generalizability, and impact on patient care.

At the same time, CAD - Computer Aided Diagnosis is used in different research and is considered an attractive study to diagnose AD. It is important to work on multiple integrations of DL [14, 15] or ML techniques, and most of the studies are concentrated on conventional DL methods for AD diagnostics. Nevertheless, most of the time, using conventional DL methods is time-consuming and complex to accumulate evidence from different modalities, and few of the modalities do have radioactivity side effects. To resolve this kind of complexity, MRI -Magnetic Resonance Imaging [16] is used in the functionality of AD diagnostics. Eventually, the MCI - mild cognitive disorders [17] and AD researchers utilize single-data modality in order to make a prediction of such stages. The amalgamation of multiple modalities of data enables a comprehensive view analysis of AD staging. Thus, DL-based methods of analyzing clinical data, genetics, and imaging for classification increase the findings in AD diagnosis. Certainly, denoising auto-encoders are used in feature extraction generated from genetic and clinical data and 3D-CNNs are utilized for data imaging. Moreover, various DL models such as k-nearest neighbour (kNN), random forest (RF), decision tree (DT), and support vector machine (SVM) are used in various researches for the diagnosis of AD [18]. The paper's main aim is to develop an effective technique for the detection of AD [19] based on a novel segmentation of brain MRI using enhanced deep learners.

In our current research, people who are affected by AD are predicted, and we mainly focused on identifying the count of Alzheimer patients with novel effective method that resolve the image classification issues and identify at an early stage. The dataset on AD has been collected from the public domain with the images including AD - 4360, CN - 4175, and MCI - 4247 images along with certain parameters such as MRI Modality, T2 Weight, T2 Weight Type consisting of Axial T2 Star, Fiel Mapping Sagittal 3D FLAIR, Axial Field Mapping 0 angle, FSE PD/T2, and AX_T2_STAR. These datasets are utilized in the training process by utilizing ML algorithms in the research. Eventually, the AD overview based on certain criteria has been evaluated in the current study. Here, in this study we have utilized a novel and improved Fast RCNN method using Bayesian Optimization for Image Segmentation process. Therefore, to solve the issues persist on image classification has been resolved with CNN and variants including VGG16, and these are achieved state-of-the-art performance evaluated in different tasks. The above-mentioned novel proposed technique has been utilized in order to detect the AD affected patients that are based on a novel segmentation process occurred in brain MRI using enhanced deep learners. These proposed techniques with Bayesian Optimization techniques have been compared with certain performance metrics that includes accuracy, precision, recall, F1-score, and MAP - Mean Average Precision with the existing techniques such as SVM - Support Vector Machine and MobileNetV2.

The different sections of the current research have been followed: Section 2 defines the Literature Review on identifying AD using various DL or ML algorithms. Section 3 represents the Research methodology on the data analysis and integration of DL or ML techniques. Section 4 defines the Implementation section with a detailed analysis of the proposed deep CNN model, especially for accurate hippocampus segmentation of brain MRI images. Section 5 defines the Results and Discussions and defines the various performance metrics of ML models. Finally, Section 6 defines the conclusion and future work of the work.

2. LITERATURE REVIEW

In study [20], the InceptionV3 and DenseNet201 architectures are trained in the research utilizing ImageNet in accordance with the DSB - Digital Subtracted Angiogram that exhibited cerebral blood flow features. The datasets are acquired from K.A.U.H hospital, consisting of digital information on Angiograms of specific participants predicted with AD. Since every scan consists of multiple frames for the right and left ICA's, the preprocessing steps were employed to use the datasets ready for classification and feature extraction. The noises from multiple frame scans were modified from real-space to Discrete Cosine Transform - DCT in order to eradicate it. Once the image was converted to the real space, the right and left ICA's were filtered using Meijering, focused on a single image. Various pre-trained techniques such as DenseNet201 and InceptionV3 are used for feature extraction, and eventually, the accuracy results are procured with 99.14%. However, FDG-PET and PET concepts have drawbacks due to the patient's head movement in scanning, creating artifacts that result in erroneous interpretation.

In study [21], a fuzzy-based segmentation method has been developed for brain MRI images. Therefore, the structuring element for the grayscale opening that transforms MRI test scans has been used to improve the brain lateral ventricle region, including significant data for MCI - mild cognitive impairment. These techniques pick edge pixels and identify the edge pixel that occurred in the next level. This technique was validated on different ADNI brain images of various orientations and subjects. Finally, the experimental results predict a promising enhancement in object boundary detection and improve the contrast quantitatively and qualitatively.

In study [22], DL, computer-aided detection, and computer intelligence advancement has been promptly developed in AD diagnosis and brain segmentation. Even though DL methods generate a greater impact on the Brain MRI quantitative analysis, it is complex to identify the generic method. Furthermore, post-processing and preprocessing initialization have the possibility to impact the DL-technique performance. In the existing research, state-of-the-art studies, especially on brain classification and structure of brain MRI in predicting AD. Therefore, the utilization of brain segmentation enhances AD classification performance. Every brain MRI segmentation assists in facilitating AD classification and interpretation. However, the MRI segmentation of the brain was challenging because the images considered low contrast, partial-volume impacts, and noisy background.

In study [23], a DNN - deep neural network model has been utilized in order to predict individuals during the risk development of AD. Therefore, MMDNN - multi-scale and multi-model DNN has been integrated with multiple scales of data taken from different regions in the brain gray matter procured from different modalities such as FDG-PET and T1-MRI. The demonstration of the utilized techniques was compared with other state-of-the-art techniques based on the discriminating task that occurred between pMCI - probable MCI and sMCI - stable MCI individuals. Hence, the classifiers are trained to differentiate subjects with the clinical diagnosis of pMCI and pNC subjects. Eventually, the samples such as sAD, pMCI, and pNC sample integration were identified and yielded an accuracy of 82.4% and 94.23% sensitivity.

Nevertheless, during the recognition tasks, the database includes large heterogeneity images that indicate the brain, images obtained with the same scale, and pose that indicates less heterogeneity.

In study [24], ensemble classifier and cross-validation have been utilized to accurately diagnose different brain diseases such as AD with the GAN strategy and multiscale feature fusion. Therefore, this technique achieved 88.28% accuracy, and the experiments have been demonstrated on MRI images (1,954) with salient observations. This technique has the possibility to study regarding the latent pattern taken from various feature types such as cortical thickness and volumes extracted at certain coarse-to-fine scales. Normally, GAN has been used for DA - data augmentation helps to overcome overfitting issues and enhance classification performance. Finally, the ensemble classifier performs better than the individual classifier. For image classification issues, CNN has been used with variants including VGG16, Inception, ResNet, and ResNet has obtained state-of-the-art performance in different tasks. Nevertheless, the network, needed a large number of samples during the training, which was labeled.

In study [25], a multimodal MRI analytical technique based on CNN was inappropriate for MRI data analysis which is single-type. Firstly, the connectivity of the human network was extracted from MRI data on multimodal has been utilized as the input for CNN. The main benefit of the integration of MRI data on multimodal via CNN kernel is obtaining higher accuracy of classification. The experimental results showed that the finding of AD with classification accuracy procured 92.06% while utilizing the multimodal MRI information that was efficient.

In study [26], the ML-techniques such as DL, ANN - Artificial Neural Network, and SVM have been used in order to diagnose AD. This research has also discussed other techniques such as multikernel learning, ensemble, and transfer learning. Therefore, compared to other techniques, SVM-based models are broadly utilized in the medical field to identify the severity of AD. Furthermore, the methods like ANN suffer from limitations such as local minima that were not found in SVM. On the other side, the ANN was more robust and versatile due to its modelling, high-dimensional space, and incremental learning. Hence, it is suggested that using ANN-based models provides better results with effective accuracy.

In study, the CNN model has been utilized in order to develop a framework that is utilized to identify certain AD characteristics taken from MRI images. In this research, 4-stages are considered to develop high-resolution probability maps to find diseases, especially from the local brain structure, for accurate prediction [27]. These early prediction concepts will help to avoid certain issues caused due to class imbalance. The Kaggle datasets consist of MRI images with class imbalance issues This research used DEMNET - Dementia Network to identify dementia levels from MRI. Eventually, this technique obtained 95.23% accuracy, AUC - Area Under Curve of 97% when compared to existing methods. Nevertheless, the class imbalance and high model parameter in the AD classification multiclass become a drawback.

In study [28], CNN combines multi-modality data with FDG-PET and T1-MR images of the hippocampal region for AD diagnosis. The traditional ML techniques do not need to extract the feature by utilizing 3D image processing CNN manually. The performance has been validated on the trained data on paired FDG-PET and T1-MR images taken from the ADNI dataset. Furthermore, the pMCI and sMCI have been used in the research and achieved higher accuracy compared to others.

Seifallahi et al. [29] explored the use of Kinect V.2 camera data and ML to distinguish AD patients from healthy controls (HC) using the Timed Up and Go (TUG) test. Analyzing joint position data from 47 HC and 38 AD subjects, the model achieved high accuracy (97.75%) and F-score (97.67%) using significant features related to balance and gait. The results suggest that this low-cost, non-invasive tool could potentially aid in early AD detection during routine checkups, though further validation in larger cohorts is needed.

In study [30] assessed the effectiveness of an activity of daily living (ADL)-based task for detecting cognitive impairment in AD patients. It included 12 AD patients and 12 healthy older adults. Results showed excellent test-retest reliability and a strong correlation between the ADL task and the MEC-35 test for the AD group. The findings suggest that this ADL-based task is a reliable tool for detecting cognitive impairment and could potentially help maintain cognitive function and prevent dementia.

In study [31] shows that a surface-based hippocampal morphometry system can effectively distinguish cognitively unimpaired individuals with different plasma NFL levels, outperforming traditional hippocampal volume measurements. With an accuracy of 86%, it demonstrates that hippocampal shape changes are linked to plasma NFL levels, offering insights into cognitive decline at the preclinical stage.

Different pretrained methods, VGG-16, CNN, and preprocessing methods such as Gray_Scale conversion, Erosion, ROI, and CLACHE are utilized in the experimentation process. GLCM has been used as a feature extraction technique with eight features that include contrast, dissimilarity, energy, entropy, homogeneity, max_GLcm_max, mean, and standard deviation [32]. Furthermore, the segmentation methods are used in the research of the Faster RCNN with Bayesian Optimization in order to predict the advancement in object boundary identification and enhance the efficiency [33]. The main utilization of this proposed method is to execute the early prediction of patients that are affected by AD to avoid some life-threatening issues because of class imbalance [34].

3. RESEARCH METHODOLOGY

In the current research, a novel and improved Fast RCNN - Region-based Convolutional Neural Network using Bayesian Optimization method are utilized for Image Segmentation process. In order to resolve the image classification issues, CNN has been used with variants, including VGG16 and it has obtained state-of-the-art performance in different tasks. The proposed technique has been utilized for the detection of AD based on a novel segmentation of brain MRI using enhanced deep learners. Furthermore, the Faster R-CNN with Bayesian Optimization technique has been compared in terms of certain performance metrics such as accuracy, precision, recall, F1-score, and MAP - Mean Average Precision with the existing methods such as SVM - Support Vector Machine and MobileNetV2 [35].

The proposed framework, NOVE-Seg, employs an enhanced Fast Region-based Convolutional Neural Network (FRCNN) coupled with Bayesian Optimization to achieve accurate segmentation of AD from Brain MRI data. In this section, we provide a detailed description of the Opti-FRCNN architecture, the Bayesian Optimization process, and the specific adaptations made to optimize these methods for AD MRI analysis.

3.1 Opti-FRCNN architecture

The Opti-FRCNN architecture is a variant of the standard FRCNN model, tailored to enhance the segmentation performance for AD detection on Brain MRI scans. It consists of several key components:

- Backbone Network: The backbone network, typically a pre-trained convolutional neural network (CNN) such as ResNet or VGG, serves as the feature extractor. In Opti-FRCNN, the backbone is fine-tuned on a large dataset of Brain MRI images to capture disease-specific features relevant to AD.
- Region Proposal Network (RPN): The RPN generates region proposals (bounding boxes) likely to contain AD-related abnormalities. In Opti-FRCNN, the RPN is optimized to improve sensitivity to small, subtle changes indicative of early-stage AD.
- Region of Interest (ROI) Pooling: ROIs extracted from the feature maps are resized to a fixed dimension for further processing. Opti-FRCNN employs ROI pooling techniques tailored to enhance feature representation of AD-related regions.
- Classification and Regression Heads: The classification head predicts the presence or absence of AD within each ROI, while the regression head refines the bounding box coordinates. These heads are optimized to improve both accuracy and localization precision for AD segmentation.

3.2 Bayesian Optimization process

Bayesian Optimization is utilized to fine-tune the parameters of the Opti-FRCNN model for optimal performance in AD MRI analysis. The process involves iteratively evaluating the model's performance on a validation set and updating the hyperparameters based on probabilistic models of the objective function. Specifically:

- Parameter Space Definition: The hyperparameters of Opti-FRCNN, such as learning rate, batch size, and architectural configurations, are defined within a search space.
- Initial Design: Bayesian Optimization begins with an initial design, typically generated using random or heuristic methods.
- Surrogate Model Training: A probabilistic surrogate model, such as Gaussian Process Regression, is trained to approximate the objective function based on the initial design.
- Acquisition Function Optimization: The acquisition function guides the selection of the next set of hyperparameters to evaluate based on the surrogate model's predictions and uncertainty estimates.
- Model Updating: After evaluating the model's performance with the selected hyperparameters, the surrogate model is updated, and the process iterates until convergence to the optimal hyperparameters.

3.3 Tailoring for AD MRI analysis

Both the Opti-FRCNN architecture and the Bayesian Optimization process are specifically tailored and optimized for AD MRI analysis in the following ways:

- Feature Extraction: The backbone network is fine-tuned on a large dataset of Brain MRI scans, with a focus on capturing subtle AD-related features.
- Region Proposal Optimization: The RPN is trained to prioritize regions likely to contain AD-related abnormalities, with attention to small, subtle changes indicative of early-stage AD.
- Hyperparameter Optimization: Bayesian Optimization is utilized to tune the hyperparameters of Opti-FRCNN, focusing on maximizing segmentation accuracy and robustness for AD detection. In final analysis, the NOVE-Seg framework uses the Opti-FRCNN architecture and Bayesian Optimization process designed for AD MRI analysis to accurately and robustly segment AD from Brain MRI data.

3.4 Data collection

Data Collection is considered an important factor that should be focused on in every research. In the current research, the dataset has been collected from ADNI with the important parameters that need for the experimentation process. Firstly, the data were collected from the public domain with the number of images including AD - 4360, CN - 4175, and MCI - 4247 images with certain parameters such as MRI Modality, T2 Weight, T2 Weight Type consisting of Axial T2 Star, Field Mapping Sagittal 3D FLAIR, Axial Field Mapping 0 angle, FSE PD/T2, and AX_T2_STAR.

3.5 Preprocessing

The inputs that are used in the experimentation are taken from the datasets which are collected from the public domain with certain parameters which are subjected to preprocessing. With this process, inappropriate information will be filtered from the input data. Furthermore, the uncertainties, such as unwanted noise in the input data that affects the classification accuracy during the execution, are eradicated. And this makes the data more effective and compact for further evaluation. In the current research, the preprocessing stage helps to read the images collected, and an effective pre-processing technique such as Gray_scale conversion, erosion, ROI, and CLACHE has been utilized.

3.5.1 Gray_scale conversion

The Gray_scale conversion concept helps in the preprocessing stage for images, which are collectively taken from the public domain with certain parameters. Further, the Gray_scale images are considered computationally efficient in ML models, and these images can store a single black-and-white array that needs a single convolution to be evaluated.

3.5.2 Erosion

During morphological operations, the gathered images are normally processed based on the shapes. In this study, the structure element was applied to an input image taken from the dataset in order to provide an output image. Erosion is considered one of the main morphological operations with benefits such as eroding the presented object's available boundaries and diminishing the image features. With the help of erosion, the object's size or thickness was minimized in the study in order to decrease the presented white region. This process, is executed based on the kernel size and the pixel presented near the boundary, is discarded. Moreover, the matrix function is used in odd size convolved with the captured image in the process, and the original image was measured as 0 or 1.

3.5.3 ROI

The ROI is also known as the Region of Interest that is found in an image collected from the dataset. The research functions can be used either for single or multiple ROI bounding.

3.5.4 CLACHE

Histogram equalization is considered a simple image processing technique used for global contrast adjustment of the image by updating certain pixels on the image histogram with the intensity distribution. Normally, the histogram computing concept used in the research enhances the intensities of the image pixel by spreading and distributing the pixel values with larger counts. In the current research, the CLAHE - Contrast Limited Adaptive Histogram Equalization has been applied in order to enhance the histogram equalization for high-quality output in the medical field to diagnose AD with the collected datasets. Moreover, histogram equalization has certainly been applied to MRI scans, which are utilized in the current study to enhance the radiograph's contrast. Eventually, this process will help the medical experts and radiologists to interpret the scan for an accurate diagnosis of AD effectively.

3.6 Segmentation

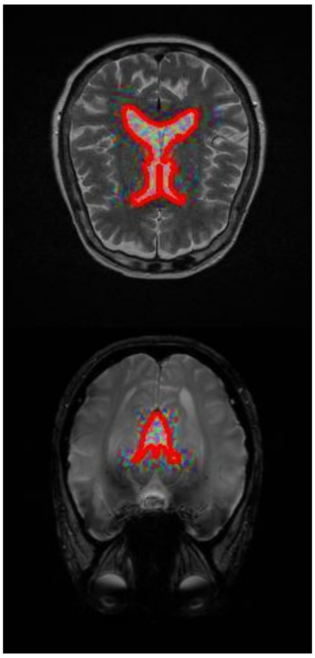
In the segmentation process, a novel segmentation model known as Faster R-CNN with Bayesian Optimization has been utilized in object detection for better accuracy output in classifying and locating the objects found in the images with certain parameters to diagnose the AD. Moreover, these algorithms are compared with other traditional methods in order to find the efficiency of the proposed method. Nevertheless, these steps include various feature extractors with requirements, and the common issues are resolved using the proposed method.

The segmentation model defines the quality of the segmentation process; hence, the segmentation process is considered an important process in the procedure of diagnosis. Generally, accurate segmentation outcomes of the provided brain tissue are achieved by the manual segmentation model exhibited by experts. Nevertheless, compared with a massive amount of datasets, the manual segmentation process becomes expensive, impractical, and time-consuming. Furthermore, because of the variations found with the knowledge and experience of the experts, the procured segmentation process is inconsistent. Therefore, the utilization of VGG-16 CNN as a pretrained method is fine-tuned by temporarily stopping certain layers from eradicating the overfitting issues. Hence, it is significant to make an accurate prediction using the proposed algorithm in the analysis process of brain MRI images that focus on the research of medical images.

Moreover, at a certain stage, the captured or acquired images will be in the deformed image and make one for easy identification. Each object is found to be effective in the detection layer, has the possibility to acquire class scores, and is coordinated with the mapping feature in the convolutional layer. The proposed technique helps to reduce the computational burden and enhance the accuracy of AD detection. In the current study, the Fast R-CNN has been applied to the region by creating a convolutional feature map. Normally, these feature maps will start with the predicted region, and then they will be modified in order to enhance and create other regions' proposals. Here, every image frame will be considered an input to the first network layer along with the predicted region proposal.

In the next step, the output procured from the first layer generally continues to the next layer with respect to another region proposal. Therefore, this proposal will continue via multiple layer networks with other identified region proposals. Furthermore, the improvement of every region proposal at every layer is formed in accordance with the ROI - Region of Interest offset value. Here, the work region proposal was identified utilizing vgg16 convolutional layers, and these layers are considered backbone layers. Next, the region proposals are transferred to ROI pooling layers and these layers will mark ROI with the colour of the hippocampus area represented in the areas of the region proposal. Finally, these models will be optimized utilizing Bayesian Optimization in order to compare the performance with other traditional methods.

Furthermore, internal brain images that depict various imaging morphologies also enable the different information represented in different gray levels that appear on the provided images. Based on the collected gray level, it has been generally divided into 4-types such as white, black, gray, and off-white. In the experimentation process, three modalities have been presented on MR images that are normally defined for the diagnosis of the clinical process that includes T1 (spin-lattice-relaxation), T2-Flair (fluid-attenuation inversion recovery), T2(Spin-spin relaxation). Certainly, T1 images are good at observing certain significant structures that define white and gray matter in the brain; T2 - images represented are used in order to locate changes; T2-Flair indicates the lesions' location with water suppression. Finally, the segmented results of the three modalities have been depicted in Figure 1.



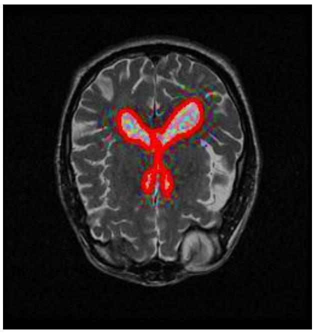


Figure 1. Segmented results

3.7 Feature extraction

In the feature extraction method, the images are extracted, which is considered a significant part of the proposed model. In the current research, the GLCM - Gray Level Co-occurrence matrix textured feature has been utilized; therefore, the neighbouring co-occurrence gray level of the image has been evaluated utilizing the square matrix based on the region of Interest (ROI) dimension with the gray levels presented in the MRI images. In this paper, we have used 8 features that include contrast (cont), dissimilarity (diss), energy (ene), entropy (ent), homogeneity (homo), ma (glcm_mx), mean (mean), and standard_deviation (std). In other words, the commonly utilized GLCM features in the research include Energy, Entropy, Homogeneity, Inertia, correlation, shade, Prominence, and Variance. The mathematical expression of GLCM features has been mentioned below:

Homogeneity

$$\text{Homogeneity (homo)} - \sum_{j,k=0}^{S-1} (P_{jk}/\ 1 + (j-k)^2) \tag{1}$$

Contrast

$$\text{Contrast (cont)} - \sum_{j,k=0}^{S-1} P_{jk}\ (j-k)^2 \tag{2}$$

Mean

$$\text{Mean (mean)} - \mu_j \sum_{j,k=0}^{S-1} j(P_{jk})\mu_j = \sum_{j,k=0}^{S-1} k(P_{jk}) \tag{3}$$

Dissimilarity

$$\text{Dissimilarity (diss)} - \sum_{j,k=0}^{S-1} P_{jk}\ |j-k| \tag{4}$$

Energy

$$\text{Energy (ene)} - \sum_{j,k} P(j,k)^2 \tag{5}$$

Standard Deviation

$$\text{Standard Deviation (std)} - \sigma_j^2 - \sum_{j,k}^{S-1} P_{jk}(j-\mu_j)^2 = P_{jk}(k-\mu_k)^2\ \ \sigma_j = \sqrt{\sigma_j^2; \sigma_k} = \sqrt{\sigma_k^2} \tag{6}$$

Entropy

$$\text{Entropy (ent)} - \sum_{j,k=0}^{S-1} P_{jk}(-\ln P_{jk}) \tag{7}$$

Correlation

$$\text{Correlation(corr)} - P_{jk}\left[(j-\mu_j) - (j - \mu_k)\ /\ \sqrt{(\sigma_j^2)(\sigma_k^2)}\ \right] \tag{8}$$

The above-represented mathematical expression indicates the probability values of j and k taking place in the original image (adjacent pixels) presented in the window, indicating the neighborhood. j and k are defined as the rows and columns of the GLCM. Due to the development of the GLCM, j defines the DN, which is the digital number that indicates the target pixel value, and K is the DN value of the neighbor. The correlation equation defines the Mean and indicates the standard deviation.

A detailed comparative analysis was performed against Support Vector Machine (SVM) and MobileNetV2 to validate the suggested NOVE-Seg framework for AD detection utilizing Opt-FRCNN on Brain MRI. Test setup, performance indicators, and statistical significance are described here.

4. EXPERIMENTAL SETUP

Datasets: The experiments were conducted on a publicly available dataset of Brain MRI scans, containing a diverse range of AD and non-AD subjects. The dataset was divided into training, validation, and test sets following standard protocols.

Preprocessing: Prior to training and testing, the MRI images underwent preprocessing steps, including normalization, skull stripping, and spatial normalization to ensure consistency and remove non-brain tissues.

Implementation Details: The NOVE-Seg framework was implemented using Python and popular DL libraries such as TensorFlow or Pytorch. The Opti-FRCNN architecture was trained on the training set and fine-tuned using Bayesian Optimization, while hyperparameters were optimized using cross-validation on the validation set.

4.1 Performance metrics

Accuracy: The primary performance metric used to evaluate the effectiveness of the proposed framework was accuracy, which measures the proportion of correctly classified AD and non-AD subjects.

Sensitivity and Specificity: Sensitivity (true positive rate) and specificity (true negative rate) were also calculated to assess the framework's ability to detect AD cases while minimizing false positives.

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): AUC-ROC provides a comprehensive measure of the classifier's ability to discriminate between AD and non-AD subjects across different thresholds.

4.2 Comparative analysis

Baseline Methods: The performance of NOVE-Seg was compared against two baseline methods: SVM and MobileNetV2. SVM is a traditional ML algorithm commonly used for classification tasks, while MobileNetV2 is a lightweight convolutional neural network architecture designed for mobile and embedded devices. Evaluation: The proposed framework and baseline methods were evaluated using the same dataset and under identical experimental conditions to ensure a fair comparison.

Statistical Significance: Statistical tests, such as paired t-tests or Wilcoxon signed-rank tests, were conducted to assess the statistical significance of performance differences between NOVE-Seg and baseline methods.

4.3 Performance discussion

Quantitative Results: The comparative analysis yielded quantitative results in terms of accuracy, sensitivity, specificity, and AUC-ROC for each method.

Qualitative Analysis: Qualitative insights into the strengths and weaknesses of each method were provided, including visualizations of segmentation results and clinical relevance.

Statistical Significance: The statistical significance of performance differences between NOVE-Seg and baseline methods was reported, highlighting the superiority of the proposed framework.

The comparative study section compares the NOVE-Seg framework to existing approaches to assess its performance, statistical significance, and clinical implications for AD identification utilising Brain MRI data.

4.4 Dataset description

The dataset utilized in this study consists of Brain MRI images acquired from subjects diagnosed with AD, Cognitive Normal (CN), and Mild Cognitive Impairment (MCI).

Curatorial Process: The dataset was meticulously curated from publicly available repositories and clinical databases to ensure diversity and representativeness of AD-related pathology. The selection process involved rigorous quality control measures to minimize bias and ensure the reliability of the data.

Demographic Information: Comprehensive demographic information of the subjects, including age, gender distribution, clinical diagnosis, and relevant medical history, was recorded and utilized for subgroup analyses and stratification during data preprocessing and analysis. Image Acquisition Parameters: detailed information regarding the MRI acquisition parameters, such as field strength, voxel size, imaging sequences (e.g., T1-weighted, T2-weighted), and imaging protocols, was documented to facilitate reproducibility and comparability of results across different imaging centers and studies.

4.5 Data preprocessing

Normalization: Prior to model training and testing, the MRI images underwent intensity normalization to correct for inter-subject intensity variations and enhance comparability between scans. Skull Stripping: Non-brain tissues, including the skull and scalp, were removed from the MRI images using validated skull stripping algorithms to isolate the brain region for subsequent analysis. Spatial Normalization: Spatial normalization techniques, such as affine registration or nonlinear warping, were applied to align the MRI scans to a common anatomical template (e.g., MNI152) to account for inter-subject anatomical variability.

4.6 Experimental design

Training, Validation, and Test Sets: The dataset was randomly partitioned into training, validation, and test sets using stratified sampling to ensure balanced representation of AD, CN, and MCI subjects across subsets. Cross-Validation: To mitigate overfitting and evaluate the generalization performance of the NOVE-Seg framework, k-fold cross-validation (typically k = 5 or k = 10) was employed, with hyperparameter tuning conducted on the validation set.

The dataset and performance metrics component includes dataset characteristics, data preparation, performance evaluation measures, experimental design, and ethical considerations. Transparency, reproducibility, and validity of study conclusions depend on these details.

4.7 Classification

The classification process will be executed after the feature extraction with the CNN classification with certain features, including layer type, output shape, and parameters represented in Table 1.

Table 1. CNN classification with certain features

Layer Type	Output Shape	Parameters
conv2d (Conv2D)	(None, 255, 255, 32)	896
leaky_re_lu (LeakyReLU)	(None, 255, 255, 32)	0
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18496
leaky_re_lu_1 (LeakyReLU)	(None, 128, 128, 64)	0
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 128)	73856
leaky_re_lu_2 (LeakyReLU)	(None, 64, 64, 128)	0
max_pooling2d_2 (MaxPooling_2D)	(None, 32, 32, 128)	0
flatten (Flatten)	(None, 131072)	0
dense (Dense)	(None, 128)	16777344
leaky_re_lu_3 (LeakyReLU)	(None, 128)	0
dense_1 (Dense)	(None, 3)	387

The layer type utilized in the study includes conv2d (Conv2D), leaky_re_lu (LeakyReLU), max_pooling2d (MaxPooling2D), conv2d_1 (Conv2D), leaky_re_lu_1 (LeakyReLU), max_pooling2d_2 (MaxPooling_2D), flatten (Flatten), dense (Dense), leaky_re_lu_3 (LeakyReLU), and dense_1 (Dense) with the output shape and parameters represented in Table 1. The total parameters used in the study are 16,870,979, trainable parameter 16,870,979, and non-trainable parameter 0. The Bayesian hyperparameters have been utilized in the current research with the proposed Faster R-CNN method as an optimization technique. The datasets have been taken from the public domain, and the proposed Faster R-CNN method with Bayesian Optimization procures efficient results with better accuracy and sensitivity.

4.8 Implementation of Opti-FRCNN model

The Implementation section defines a detailed analysis of the proposed deep CNN model for accurate hippocampus segmentation of brain MRI images. The proposed Opti-FRCNN model has been utilized for image segmentation, and the block diagram of the technique has been explained in Figure 2.

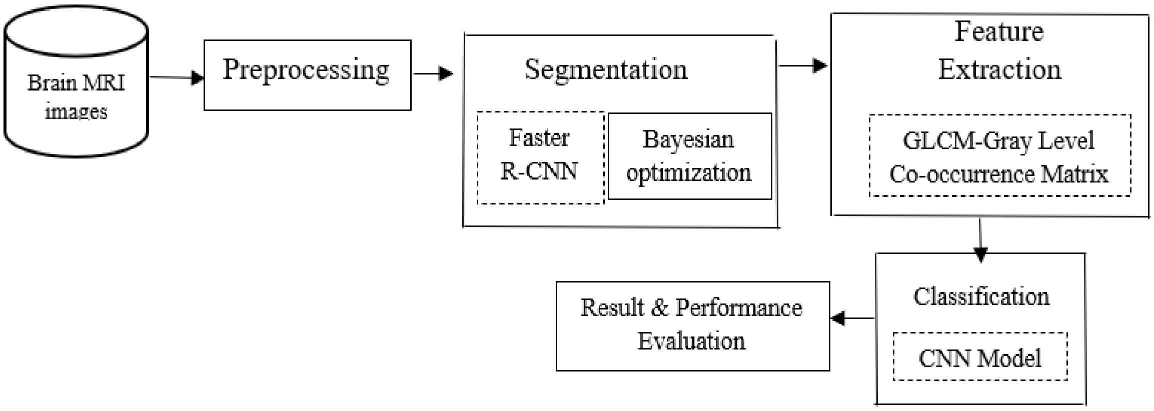


Figure 2. Architecture of the proposed Opti-FRCNN method

The proposed method is considered as a region by generating a convolutional feature map that enables the region proposal prediction process that is generally modified and improved in order to create other region proposals with the patients' collected image frames applied on the network layer. Therefore, the first layer output continues the process to the next layer with the help of the other region's proposal. The CNN formula has been mentioned below:

$$\text{Wout} = \frac{W - F + 2P}{S} + 1 \tag{9}$$

P - Padding, S - Stride, F - Size of spatial, Wout - Output Volume Size and the mathematical expression of Fast-RCNN have been mentioned below:

$$\begin{aligned}\text{Multi} - \text{task Loss (MTL)} \\ &= -\text{L}\ (\text{q}, \text{r}, \text{s}^{\text{t}}, \text{u}) - \text{Lcls}\ (\text{q}, \text{r}) \\ &+ \lambda[\text{r} \geqslant 1]\text{Lloc}(\text{s}^{\text{t}} - \text{v})\end{aligned} \tag{10}$$

$$\text{Lcls} - (\text{q}, \text{r}) = -\log \text{q}_{\text{r}} \tag{11}$$

$$\text{Lloc}(\text{s}^{\text{t}}, \text{u}) - \sum_{\text{j} \in \{\text{y,z,w,h}\}} \text{smooth}_{\text{L1}}(\text{s}^{\text{t}} - \text{u}_{\text{j}}) \tag{12}$$

$$smooth_{L1}(y) - \begin{cases} 0.5\, y^2 \; if \; |y| < 1 \\ |y| - 0.5 \; otherwise \end{cases} \tag{13}$$

Lcls - log loss for class q that is true; Lloc - bounding box loss function; [q > = 1] – q = 0 - background class, and it is equal to one during q > = 1. w - width of maximum pooling and h - the height of maximum pooling. L - VGG16, y and z - loss position.

The work region proposal is identified utilizing VGG16 convolutional layers, which are considered backbone layers. The improved fast RCNN utilizes Bayesian Optimization for the Image segmentation process. The main steps included in the process are as follows:

- Firstly, the IoU-Intersection over Union has been computed along with the ground truth values. The computed IoU will be represented as follows:
  IoU - Area of the Intersection / Area of the Union
- The input image is fed to the VGG16 using Fast RCNN that develops the convolutional feature maps. The maps are used in the regions with the extracted data.
- Here, in case the IoU is greater than or equal to 0.5, it is considered as an ROI - region of interest. Otherwise, there is a possibility of neglecting the particular region. These will have proceeded to all the regions and then the selected set of regions for the IoU greater than 0.5.

Next, the RoI pooling layer has been utilized in order to reshape all proposed regions into a fixed size. After that, the specified affected place will be extracted from the pooling layer ROI that will be marked with colour border. The utilized proposed model will be hyper-tuned with Bayesian Optimization. The mathematical expression of Bayesian Optimization has been mentioned below:

$$\text{P}(\text{C}|\text{D}) - \frac{\text{P}(\text{D}|\text{C}).\,\text{P}(\text{C})}{\text{P}(\text{D})} \tag{14}$$

P(C|D) - probability of C occurring with the provided evidence D, which has occurred previously; P(D|C) - probability of D occurred with the provided evidence C, which has occurred previously; P(C) - probability of C occurring; P (D) - Probability of D occurring.

4.9 Integration into clinical workflows

The NOVE-Seg framework may help detect AD early in Brain MRI scans. NOVE-Seg can automate the segmentation and classification of AD-related anomalies, helping radiologists and neurologists diagnose faster and spend resources more efficiently. NOVE-Seg integration into clinical pipelines could enable faster interventions and personalised AD treatment regimens, improving patient results and quality of life.

4.10 Result on patients

The framework's ability to properly detect AD from Brain MRI data has major implications for patient care and management. Early and correct AD diagnosis allows for the timely introduction of pharmaceutical, cognitive, and lifestyle interventions that slow disease progression and relieve symptoms. NOVE-Seg may also help patients and carers make educated long-term care planning, financial, and support service decisions by promoting early detection, improving patient well-being and quality of life.

4.11 Clinical validation/feedback

To evaluate the NOVE-Seg framework's usability, reliability, and generalizability in clinical situations, radiologists, neurologists, and other healthcare experts must validate it. Domain specialists can advise on the framework's performance, usability, and integration issues, guiding iterative changes to maximise clinical utility. Retrospective and prospective cohorts of AD, CN, and MCI patients can also validate the framework's diagnostic accuracy, sensitivity, specificity, and clinical impact in varied patient populations. The NOVE-Seg architecture may improve AD identification and diagnosis utilising Brain MRI data. Its integration into clinical operations may improve patient outcomes and streamline healthcare. However, extensive clinical validation and feedback from healthcare professionals are needed to assure its efficacy, dependability, and scalability in clinical practice.

5. RESULTS AND DISCUSSIONS

A novel and improved Fast RCNN-Region-based Convolutional Neural Network using the Bayesian Optimization method for the Image Segmentation process has been proposed in the current study. In order to resolve the image classification issues, CNN has been used with variants, including VGG16 has obtained state-of-the-art performance in different tasks. The proposed technique has been utilized for the detection of AD based on a novel segmentation of brain MRI using enhanced deep learners.

5.1 Performance evaluation

The performance of the proposed technique has been compared with the existing techniques based on certain parameters in order to determine the efficiency of the proposed techniques in terms of accuracy and sensitivity. In the current study, the Faster R-CNN with Bayesian Optimization technique has been compared in terms of certain performance metrics such as accuracy, precision, recall, F1-score, and MAP - Mean Average Precision with the existing methods such as SVM - Support Vector Machine and MobileNetV2 has been mentioned in Table 2. Moreover, the training and validation accuracy and loss of the CNN model with epochs have been represented in the graphical representation in Figure 3 and Figure 4. The training and validation accuracy and loss of the MobileNetV2 model with epochs have been represented in the graphical representation in Figure 5 and Figure 6. Finally, the comparison table of the proposed technique with the classification algorithms is depicted in Figure 7 and Table 2 based on the performance metrics such as accuracy, precision, recall, F1-score, and MAP - Mean Average Precision. The accuracy has been measured with the actual true classifications.

Accuracy = TP + TN / Total number of samples

TP - True Positive, TN - True Negative

Precision = TP / (TP + FP)

TP - True Positive, FP = False Positive

Recall = TP / (TP + FN)

FN - False Negative

F1 - Score = 2 × (Precision x Recall) / (Precision + Recall)

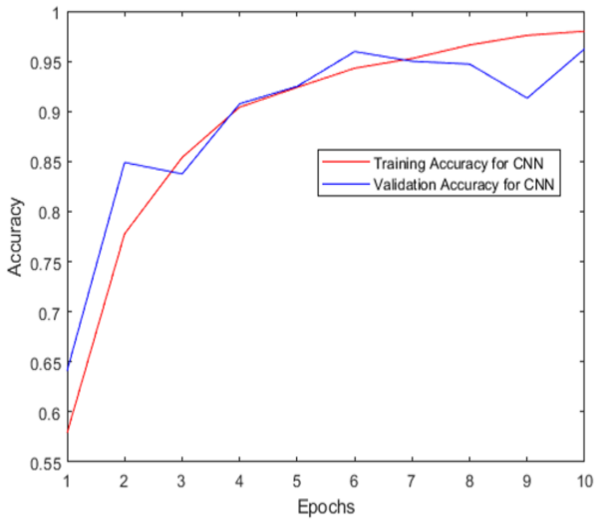


Figure 3. Training and validation accuracy of CNN

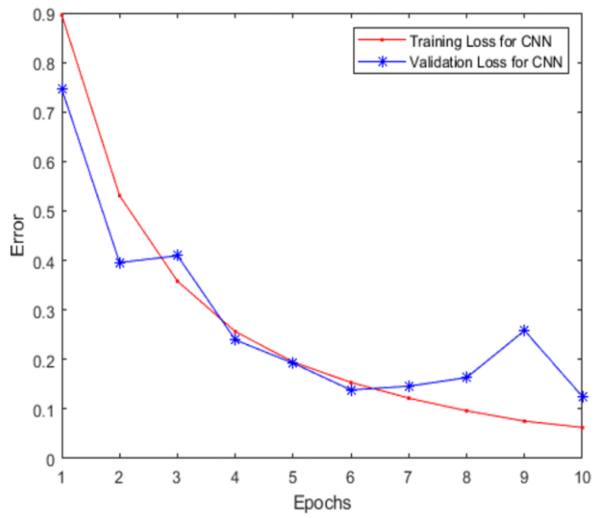


Figure 4. Training and validation loss of CNN

Table 2. Performance evaluation of the proposed methods against existing classification algorithms

Model_Name	Accuracy	Precision_Score	Recall_Score	F1 Score	MAP (Mean Avg Precision)
SVM	0.894444444	0.8946895830	0.894434031	0.894338650	0.311242651
Mobile_Net_V2	0.811805555	0.822003754	0.811996470	0.808296818	0.81630126
Proposed Model (CNN)	0.9625	0.964806529	0.962358449	0.962614487	0.96230424

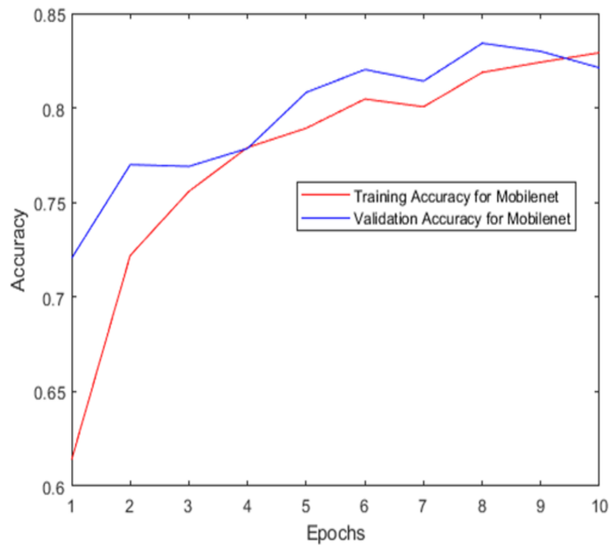


Figure 5. Training and validation accuracy of MobileNet2

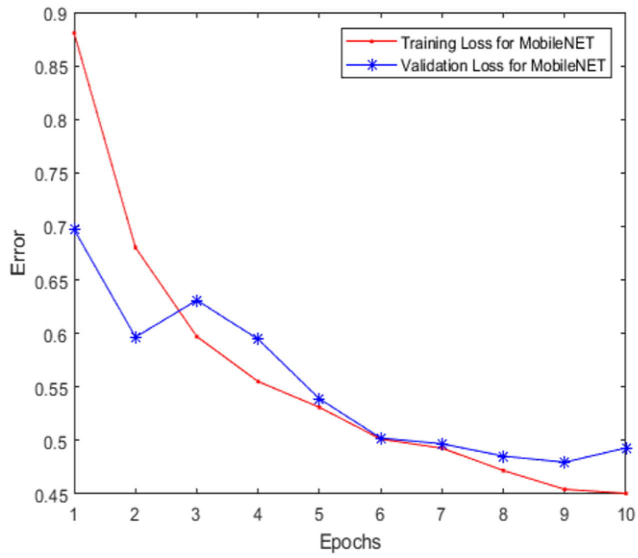


Figure 6. Training and validation loss of MobileNetV2

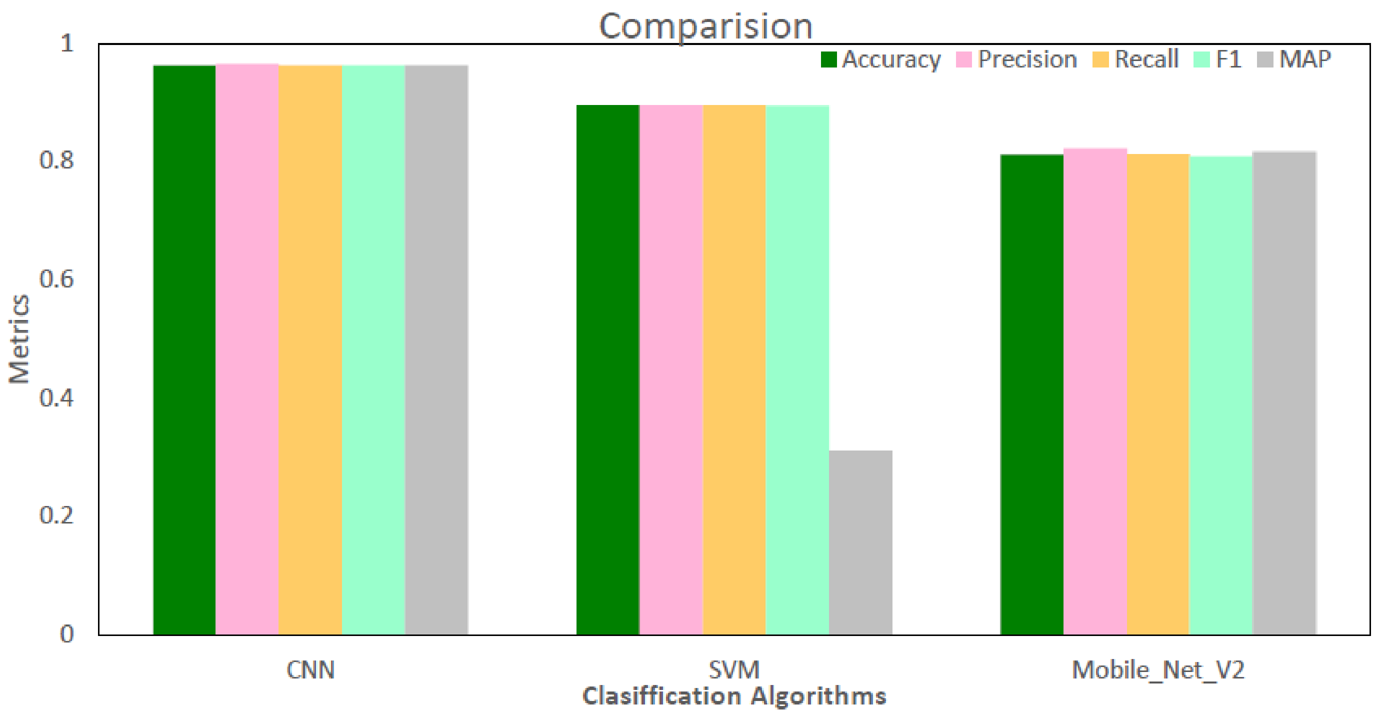


Figure 7. Comparison of the proposed method with existing classification algorithms

6. CONCLUSION AND FUTURE WORK

The main focus of the research study is to develop an improved Fast RCNN - Region-based Convolutional Neural Network using the Bayesian Optimization method for the Image Segmentation process. Therefore, the image classification issues are resolved with the CNN method, and its variants, including VGG16, have obtained state-of-the-art performance in different tasks. The proposed technique has been utilized for the detection of AD based on a novel segmentation of brain MRI using enhanced deep learners. Furthermore, the Faster R-CNN with Bayesian Optimization technique has been compared in terms of certain performance metrics such as accuracy of 96%, precision of 96%, recall of 96%, F1-score of 96%, and MAP - Mean Average Precision of 96% with the existing methods such as SVM - Support Vector Machine and MobileNetV2. In future, the large real-time datasets will be used with the integration of the proposed system in order to enhance the accuracy and sensitivity.

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