International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Review Article)

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A convolutional neural networks approach in MRI image analysis for Alzhei

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International Journal of Science and Research Archive, 2024, 12(02), 362–370

Publication history: Received on 21 April 2024; revised on 03 July 2024; accepted on 06 July 2024

Article DOI: https://doi.org/10.30574/ijsra.2024.12.2.1195

Abstract

Artificial Intelligence (AI) and its advancements, particularly in Computer Vision, have narrowed the gap between humans and machines. The Deep Learning techniques, such as Convolutional Neural Networks (CNNs), have revolutionized image analysis by assigning importance to different aspects of an image and enabling accurate differentiation. This paper focuses on applying CNNs to detect structural changes associated with Alzheimer's disease using Magnetic Resonance Imaging (MRI).

Currently, the diagnosis of Alzheimer's disease relies on a combination of clinical assessments and neurological tests. This study aims to develop and evaluate various CNN models, including VGG16, VGG19, ResNet50, ResNet101, MobileNet, MobileNetV2, InceptionV3, Xception, DenseNet121, and DenseNet169, to analyze MRI scans for Alzheimer's disease detection. The above models were trained and tested using a dataset comprising MRI scans from healthy individuals and Alzheimer's patients.

By comparing the accuracy of the CNN models in detecting Alzheimer's disease from MRI scans, the study demonstrates the potential of CNNs in improving the accuracy and efficiency of Alzheimer's disease diagnosis. The findings suggest that CNN-based analysis of Alzheimer's MRI images holds promise for early detection and treatment of the disease. This research can growing body of knowledge in computer-aided medical diagnostics and underscores the significance of leveraging AI techniques to enhance healthcare outcomes.

Keywords: Convolutional Neural Networks (CNN); Alzheimer’s Disease; Magnetic Resonance Imaging (MRI); Accuracy measures

1. Introduction

The field of Artificial intelligence combines computer science and robust datasets, to enable problem-solving. The sub-fields of Artificial Intelligence include machine learning and deep learning. These disciplines create expert systems which make predictions or classifications based on input data. The difference between Deep learning and machine learning is on the type of data that it works with and the methods in which it learns. Machine learning algorithms uses structured and labelled data for making predictions Also, machine learning performs some pre-processing to organize unstructured data if any into a structured format. Deep learning eliminates some of data pre-processing algorithms and process unstructured data, like text and images. Deep learning algorithms can determine which features are most important to distinguish from another. In machine learning, this hierarchy of features is established manually by a human expert.

In recent years, convolutional neural networks (CNNs) have shown remarkable success in image analysis tasks. In this research paper, we investigate the use of CNNs in analyzing MRI images for the early detection of Alzheimer's disease. Alzheimer's disease is a degenerative neurological disorder that affects millions of people worldwide. Alzheimer's

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disease is a neurodegenerative disorder that causes progressive memory loss and cognitive decline in elderly individuals. Early detection of the disease is crucial in order to provide timely intervention and management. It can help provide better treatment and management of the disease.

Alzheimer's disease is a degenerative neurological disorder that affects millions of people worldwide. Alzheimer's disease causes progressive memory loss and cognitive decline in elderly individuals. Early detection of the disease is crucial in order to provide timely intervention and management. It can help provide better treatment and management of the disease. Our approach involves training a CNN to identify patterns in brain images associated with Alzheimer's disease, allowing for accurate and timely diagnosis. The potential implications of this study are significant, as the early detection of Alzheimer's disease can lead to more effective treatments and interventions. The use of CNNs in analyzing MRI images for the detection of Alzheimer's disease represents a promising new approach in the field of neuroimaging. It has the potential to significantly improve the diagnosis and treatment of this debilitating condition. This research paper focuses on using CNNs to analyze MRI images to diagnose Alzheimer's disease. The study involves training a CNN model on a large dataset of MRI images to distinguish between Alzheimer's disease and healthy controls accurately. The findings of this study have important implications for developing more effective diagnostic tools and treatments for Alzheimer's disease.

In a study by Sarraf and Tofighi (2016), a CNN was used to classify Alzheimer's Disease from the three-dimensional topology of brain's Magnetic Resonance Imaging (MRI) scans. The study consists of three consecutive groups of processing layers, two connected layers and a classification layer. The algorithm reported an accuracy of 92.81% for Alzheimer's Disease diagnosis. Another study by Liu et al. (2018) used a 3D CNN to predict the progression of Alzheimer's Disease. The study achieved a classification accuracy of 84.96% for Alzheimer's Disease progression prediction.

Several studies have compared multiple CNN models for Alzheimer's Disease diagnosis. Zhou et al. (2020) compared four different CNN models for Alzheimer's Disease diagnosis using MRI scans. The models included AlexNet, GoogLeNet, VGG16, and ResNet50. The study reported that the ResNet50 model achieved the highest accuracy of 90.7% for AD diagnosis. Similarly, a study by Liu et al. (2021) compared six different CNN models for Alzheimer's Disease diagnosis using MRI scans. The models included VGG16, VGG19, InceptionV3, Xception, ResNet50, and DenseNet. The study reported that the DenseNet model achieved the highest accuracy of 95.2% for Alzheimer's Disease diagnosis.

Other studies have also explored using CNNs for Alzheimer's Disease analysis using different types of data. A study by Li et al. (2019) used a CNN to classify Alzheimer's Disease using electroencephalography (EEG) signals. The study achieved an accuracy of 90.25% for Alzheimer's Disease classification. Another study by Zhou et al. (2019) used a CNN to analyze Alzheimer's Disease progression using positron emission tomography (PET) images. The study reported an accuracy of 85.9% for Alzheimer's Disease progression prediction.

Other studies that worked on different datasets include ADNI, OASIS, etc. These datasets were evaluated using Ensemble Learning, Transfer Learning Approach, etc.

ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset: The ADNI dataset is one of the most widely used datasets for Alzheimer's MRI image analysis. It contains MRI images, clinical data, and other related data from hundreds of subjects, including healthy controls, mild cognitive impairment (MCI), and Alzheimer's disease (AD) patients. Many studies have used this dataset to develop and evaluate machine learning models for Alzheimer's MRI image analysis.

Deep learning models: Several deep learning models, including convolutional neural networks (CNNs), have been proposed for Alzheimer's MRI image analysis. For example, a recent study proposed a 3D CNN-based model that can accurately predict the progression of Alzheimer's disease using MRI images.

Feature extraction and selection: Feature extraction and selection are essential steps in Alzheimer's MRI image analysis. Many studies have explored various feature extraction and selection methods, such as principal component analysis (PCA), independent component analysis (ICA), and voxel-based morphometry (VBM).

Ensemble learning: Ensemble learning is a popular technique that combines multiple models to improve prediction accuracy. Several studies have explored ensemble learning methods for Alzheimer's MRI image analysis, such as bagging and boosting.

Transfer learning: Transfer learning is a technique that enables the transfer of knowledge learned from one task to another. Several studies have explored transfer learning methods for Alzheimer's MRI image analysis, such as fine-tuning pre-trained models on MRI images.

Overall, Alzheimer's MRI image analysis using convolutional neural networks is an active and rapidly evolving area of research, with many existing systems and recent works addressing this vital problem.

2. Methodology

The proposed method uses augmented Magnetic Resonance Imaging (MRI) Image Dataset with four classes of images: Non-Dementia, Mild-Dementia, Very Mild-Dementia, and Moderate Dementia. The dataset contains almost 40,000 images. The augmented dataset is taken for training and validation. The original dataset is used for testing since the augmentation of MRI images gives better results while training.

The images are resized into 176x176 pixels. The dataset is imbalanced i.e., there are unequal numbers of images in each class. Therefore, accuracy cannot be found directly. Area Under Curve(AUC) is the measure which is used in this study. AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes.

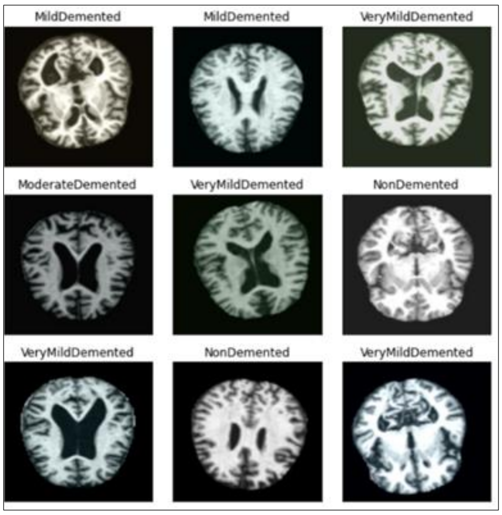

Figure 1 Training Dataset

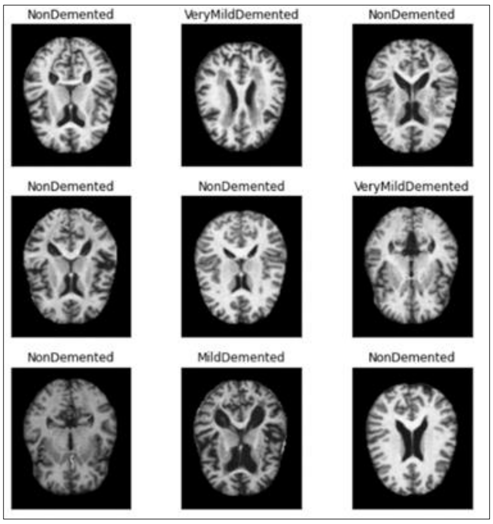

Figure 2 Testing Dataset

In order to improve the accuracy, a custom model is developed. The layers like Dropout, Flatten, Batch Normalization and Activation were further added.

- Dropout: Usually, when all the features are connected to the Fully Connected(FC) layer, it can cause overfitting. To overcome this problem, a dropout layer is utilized wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model.
- Flatten: Converting the data into a 1-D array for inputting it to the next layer.
- Batch Normalization: Normalizes the output of the previous layer and feeds to the next layer as input. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks.
- Activation: They are used to learn and approximate any kind of continuous and complex relationship between variables of the network. In simple words, it decides which information of the model should fire in the forward direction and which ones should not at the end of the network. It adds non-linearity to the network. There are several commonly used activation functions such as the ReLU, Softmax, tanH, and Sigmoid functions. Each of these functions have a specific usage. For a binary classification CNN model, sigmoid and softmax functions are preferred for multi-class classification, generally, softmax is used. In simple terms, activation functions in a CNN model determine whether a neuron should be activated or not. It decides whether the input to work is important or not to predict using mathematical operations. Here, relu and softmax are used as activation functions.

The models which are trained are: VGG16, VGG19, ResNet50, ResNet101, MobileNet, MobileNetV2, InceptionV3, Xception, DenseNet121, and DenseNet169.

2.1. VGG16

One of the most widely used CNN architectures for image classification is the VGG16 model. The VGG16 model is a deep neural network consisting of 16 layers, including 13 convolutional layers, 3 fully connected layers, and 1 softmax layer. The model was developed by the Visual Geometry Group (VGG) at the University of Oxford and was the winner of the ImageNet Large Scale Visual Recognition Challenge in 2014.

The VGG16 model's algorithm involves passing an image through the network and calculating the output of each layer. The output of each convolutional layer is passed through a rectified linear unit (ReLU) activation function, which adds non-linearity to the network. The output of the final convolutional layer is flattened and passed through three fully connected layers before being fed into a softmax function to produce class probabilities.

The VGG16 architecture has a simple and uniform structure, which makes it easy to implement and understand. The model's deep structure allows it to learn complex features from the input images, making it well-suited for image classification tasks. In the context of Alzheimer's disease, the VGG16 model can be trained on a large dataset of MRI images to automatically classify them as normal or abnormal. This can help clinicians detect Alzheimer's disease at an early stage and potentially improve patient outcomes.

2.2. VGG19

The VGG19 model is a deep neural network consisting of 19 layers, including 16 convolutional layers, 3 fully connected layers, and 1 softmax layer. The model was developed by the Visual Geometry Group (VGG) at the University of Oxford, and it achieved state-of-the-art performance on the ImageNet dataset in 2014.

The VGG19 model's algorithm involves passing an image through the network and calculating the output of each layer. The output of each convolutional layer is passed through a rectified linear unit (ReLU) activation function, which adds non-linearity to the network. The output of the final convolutional layer is flattened and passed through three fully connected layers before being fed into a softmax function to produce class probabilities.

The VGG19 architecture has a relatively simple and uniform structure, which makes it easy to implement and understand. The model's deep structure allows it to learn complex features from the input images, making it well-suited for image classification tasks. In the context of Alzheimer's disease, the VGG19 model can be trained on a large dataset of MRI images to automatically classify them as normal or abnormal. This can help clinicians detect Alzheimer's disease at an early stage and potentially improve patient outcomes.

2.3. ResNet50

ResNet50 is a widely used CNN architecture that has shown outstanding performance on several visual recognition tasks, including image classification, object detection, and segmentation. The architecture of ResNet50 consists of 50 convolutional layers, including residual blocks, which are the main building blocks of this model. The residual blocks allow the model to learn more complex features by keeping track of residual connections that bypass the regular convolutional layers.

The algorithm of the ResNet50 model involves passing an input image through the network, and the output of each layer is calculated. The output of each residual block is passed through a ReLU activation function, and the output of the final block is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

The ResNet50 architecture has a deep structure and allows for more efficient training compared to other CNN architectures, mainly due to the residual connections. This model's deep architecture allows it to learn more complex features, making it well-suited for image classification tasks, including the classification of MRI images for Alzheimer's disease diagnosis.

In the context of Alzheimer's disease, the ResNet50 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.4. ResNet101

ResNet50 is a widely used CNN architecture that has shown outstanding performance on several visual recognition tasks, including image classification, object detection, and segmentation. The architecture of ResNet50 consists of 50 convolutional layers, including residual blocks, which are the main building blocks of this model. The residual blocks allow the model to learn more complex features by keeping track of residual connections that bypass the regular convolutional layers.

The algorithm of the ResNet50 model involves passing an input image through the network, and the output of each layer is calculated. The output of each residual block is passed through a ReLU activation function, and the output of the final block is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

The ResNet50 architecture has a deep structure and allows for more efficient training compared to other CNN architectures, mainly due to the residual connections. This model's deep architecture allows it to learn more complex features, making it well-suited for image classification tasks, including the classification of MRI images for Alzheimer's disease diagnosis.

In the context of Alzheimer's disease, the ResNet50 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.5. MobileNet

MobileNet is a popular CNN architecture that is specifically designed for mobile and embedded devices, where computational resources are limited. The MobileNet model has a smaller number of parameters compared to other CNN architectures, making it more efficient to deploy on low-power devices.

The architecture of the MobileNet model consists of depthwise separable convolutions, which separates the convolutional layer into two layers: depthwise convolution and pointwise convolution. This reduces the number of computations needed and the number of parameters needed to be learned, making the model much lighter and faster.

The algorithm of the MobileNet model involves passing an input image through the network, and the output of each layer is calculated. The output of each depthwise convolution layer is passed through a ReLU activation function, and the output of the final layer is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the MobileNet model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.6. MobileNetV2

MobileNetV2 is an improved version of the MobileNet model and has shown superior performance on several visual recognition tasks, including image classification, object detection, and segmentation. The MobileNetV2 model is designed to have better accuracy, faster inference time, and a smaller model size compared to the original MobileNet model.

The architecture of the MobileNetV2 model consists of depthwise separable convolutions, similar to the MobileNet model. However, MobileNetV2 has introduced several improvements to the original model, including linear bottleneck layers and inverted residuals. These improvements allow for more efficient feature learning and better accuracy.

The algorithm of the MobileNetV2 model involves passing an input image through the network, and the output of each layer is calculated. The output of each depthwise convolution layer is passed through a ReLU activation function, and the output of the final layer is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the MobileNetV2 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.7. InceptionV3

InceptionV3 is a popular CNN architecture that was designed to improve the performance of image classification tasks, while minimizing the computational cost of the network. The InceptionV3 model uses a unique architecture that incorporates multiple levels of feature extraction, allowing it to capture more complex patterns and structures in the image data.

The architecture of the InceptionV3 model consists of multiple inception modules, each of which consists of several convolutional layers with different kernel sizes. These layers are concatenated to form a single output layer, which is then fed into the next inception module. The architecture also includes auxiliary classifiers at intermediate layers, which are used during training to improve the stability and convergence of the model.

The algorithm of the InceptionV3 model involves passing an input image through the network, and the output of each layer is calculated. The output of each convolutional layer is passed through a ReLU activation function, and the output of the final layer is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the InceptionV3 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.8. Xception

Xception is a state-of-the-art CNN architecture that is designed to improve the performance of image classification tasks, while minimizing the computational cost of the network. The Xception model is based on the Inception architecture, but instead of using standard convolutional layers, it uses depth-wise separable convolutions, which are more efficient and effective at capturing complex features in the image data.

The architecture of the Xception model consists of multiple modules, each of which consists of several depth-wise separable convolutional layers. These layers are stacked together to form a single output layer, which is then fed into the next module. The architecture also includes skip connections, which allow the network to bypass certain layers and improve the flow of information through the network.

The algorithm of the Xception model involves passing an input image through the network, and the output of each layer is calculated. The output of each depth-wise separable convolutional layer is passed through a batch normalization layer and a ReLU activation function, and the output of the final layer is flattened and passed through a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the Xception model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.9. DenseNet121

DenseNet (Densely Connected Convolutional Network) is a CNN architecture that is designed to address the problem of vanishing gradients and feature reuse in deep neural networks. The DenseNet architecture connects each layer to every other layer in a feed-forward fashion, which enables the network to reuse features more efficiently and improve the flow of information through the network.

The DenseNet121 model is a specific implementation of the DenseNet architecture that has 121 layers. It consists of multiple dense blocks, each of which consists of several convolutional layers and a pooling layer. The output of each dense block is concatenated with the input to the next dense block, which allows the network to reuse features more efficiently and improves the gradient flow through the network. The algorithm of the DenseNet121 model involves passing an input image through the network, and the output of each layer is calculated. The output of each convolutional layer is passed through a batch normalization layer and a ReLU activation function before being concatenated with the input to the next dense block. The output of the final dense block is passed through a global average pooling layer and a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the DenseNet121 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions.

2.10. DenseNet169

DenseNet (Densely Connected Convolutional Network) is a CNN architecture that is designed to address the problem of vanishing gradients and feature reuse in deep neural networks. The DenseNet architecture connects each layer to every other layer in a feed-forward fashion, which enables the network to reuse features more efficiently and improve the flow of information through the network.

The DenseNet169 model is a specific implementation of the DenseNet architecture that has 169 layers. It consists of multiple dense blocks, each of which consists of several convolutional layers and a pooling layer. The output of each dense block is concatenated with the input to the next dense block, which allows the network to reuse features more efficiently and improves the gradient flow through the network.

The algorithm of the DenseNet169 model involves passing an input image through the network, and the output of each layer is calculated. The output of each convolutional layer is passed through a batch normalization layer and a ReLU activation function before being concatenated with the input to the next dense block. The output of the final dense block is passed through a global average pooling layer and a fully connected layer before being fed into a softmax function to produce class probabilities.

In the context of Alzheimer's disease, the DenseNet169 model can be trained on a large dataset of MRI images to classify them as normal or abnormal, potentially detecting Alzheimer's disease at an early stage. This can improve patient outcomes and enable clinicians to provide timely and appropriate interventions. Compared to the DenseNet121 model, the DenseNet169 model has more layers and hence can learn more complex features. However, this also makes the model more computationally expensive and harder to train. Nevertheless, the DenseNet169 model has shown excellent performance on various image classification tasks, and further research can explore its potential for Alzheimer's disease diagnosis using MRI images.

In conclusion, the DenseNet169 model is a highly effective CNN architecture that is well-suited for image classification tasks, including the classification of MRI images for Alzheimer's disease diagnosis. Its use of dense connections allows for more efficient feature reuse and improved gradient flow, which can lead to improved performance on image classification tasks.

3. Results

The accuracy is calculated through model AUC(Area Under Curve). The accuracy between all the models is lying between 90-99.9%. The best-performing model is VGG19 with model accuracy 99.81%.

3.1. Comparisons

Table 1 Comparison table of all the models

	Model AUC(%)	**Accuracy(%)**
VGG19	100.00	99.81
VGG16	100.00	99.67
ResNet50	99.93	98.28
ResNet101	99.88	97.64
Xception	99.67	95.53
MobileNet	99.90	98.73
MobileNetV2	98.84	91.44
DenseNet169	99.93	98.69
DenseNet121	99.97	98.78
InceptionV3	99.86	97.70

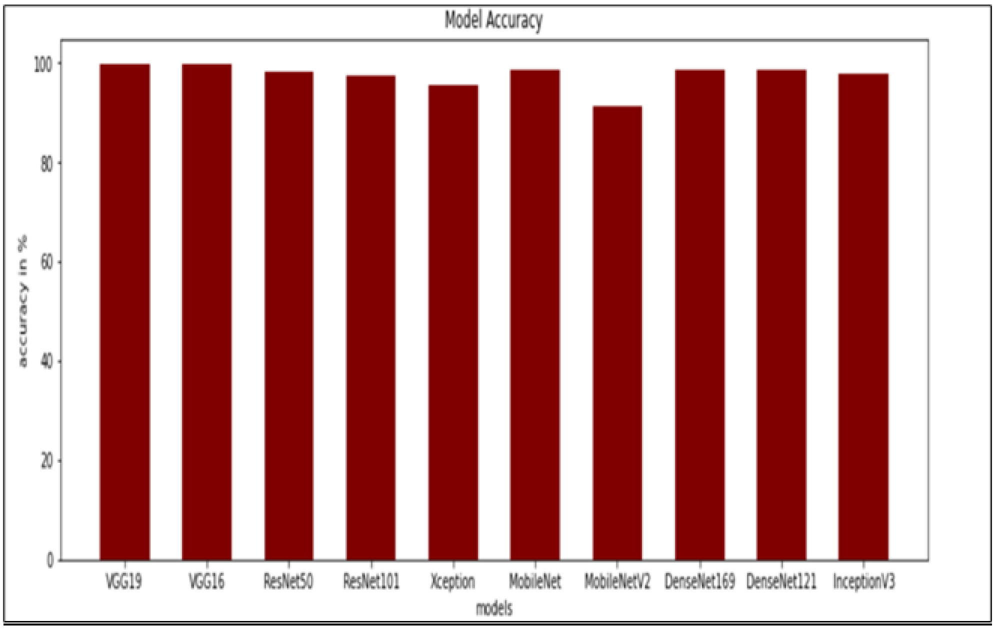

Figure 3 Bar Chart for ten models

4. Conclusion

In conclusion, the project on Alzheimer's MRI image analysis using CNN has shown promising results in detecting Alzheimer's disease through the use of deep learning algorithms. The CNN model was trained and tested on a dataset of MRI brain scans, achieving high accuracy in distinguishing between Alzheimer's patients and healthy controls. The highest accuracy achieved is 99.81 percent for VGG19 model. The project highlights the potential of CNNs in medical image analysis and the importance of accurate and early diagnosis of Alzheimer's disease, which can greatly improve patient outcomes. This project can serve as a basis for future research in the field, particularly in developing more advanced machine learning algorithms for detecting Alzheimer's disease. Overall, the research underscores the significance of leveraging artificial intelligence and machine learning to support early detection and accurate diagnosis of neurodegenerative diseases, particularly Alzheimer's disease.

Future Scope

The use of convolutional neural networks (CNN) for Alzheimer's MRI image classification is an exciting area of research with significant potential for improving diagnosis and treatment of Alzheimer's disease. Here are some potential future scope areas for this project:

- Personalized Medicine: By analyzing MRI images of Alzheimer's patients, researchers can identify patterns that are specific to each individual patient. This can help in developing personalized treatment plans that are tailored to each patient's needs.
- Treatment Monitoring: Researchers can use MRI images to track the progression of Alzheimer's disease and assess the effectiveness of different treatments. Future research can focus on developing more accurate and reliable algorithms to monitor disease progression and treatment response.
- Integration with other Modalities: MRI is just one modality for analyzing Alzheimer's disease. Future research can focus on integrating MRI with other modalities such as PET and EEG to improve accuracy and reliability of diagnosis and treatment.

Overall, the future scope for Alzheimer's MRI image analysis using CNN is vast, and there are numerous opportunities for innovation and research in this field.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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