A PROPOSED DEEP LEARNING FRAMEWORK FOR ASD DIAGNOSIS USING MRI IMAGES

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Abstract
Autism is a sneaky developmental condition characterised by delayed communication and social interaction improvement. The number of autistic children and adults is growing by the day. Because the causes of autism are unknown, early detection and intense treatment can make a significant difference. This illness causes significant behavioural changes in children and adults. With the advent of artificial intelligence, this is now achievable, potentially saving the lives of many individuals. The use of transfer learning to detect ASD in youngsters is proposed in this study. The suggested methodology detects autism using seven alternative CNN architectures: Resnet50 model , the MobileNet, Inception , VGG16, ResNet50v2 , Xception , and NasNetmobile model models . The Adam optimization methodology is a simple process that outperforms the existing method in terms of performance. As training and testing data, a dataset containing images of structural magnetic resonance imaging (sMRI) for children with autism and non-autism is provided. In comparison to seven models of architecture gave an accuracy of 0.992 for the MobileNet model.

Keywords: ASD, Deep learning , CNN , Transfer Learning , Performance Metrics.

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I.Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental illness resulting from dysfunction in the brain distinguished by early difficulties in social interactions and communication [1], [2] , as well as confined and repetitive activities. As the name implies, ASD is a collection of symptoms that reflect an overarching diagnostic category that, prior to the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [3], was made up of multiple separate disorders such as Autistic disorder, Asperger's syndrome, and other pervasive developmental disorders [4] . ASD can cause language difficulty, seizures, and other issues. ASD patients have social interaction and communication problems that are determined by numerous deep learning (DL) methods [1]. Over the last four years, the frequency of ASD in the United States has increased from one in 110 to one in 69 [5]. ASD affects around 1% of the world's population, with males being the most affected. Autism spectrum disorder (ASD) is four times as common in males than in females [6], [7] The aetiology of ASD is yet unknown, however genetics and the environment may play a role.

Early detection and successful intervention increase the quality of life for autistic people.Numerous research have looked into cerebellar anomalies [4] , grey matter (GM) volumes , and brain functional connections [8] . Obtaining sMRI image involves less time and effort from patients and physicians than other MRI procedures such as fMRI. Structural MRI (sMRI) is the most extensively used imaging modality for screening anatomical defects in both research and clinical usage[9], sMRI, or structural magnetic resonance imaging, is an advanced brain scanning method that allows experts to closely scrutinize the brain's anatomical details. and when it comes to structural MRIs, two things stand out: (1) shape and (2) volumetric features [10].

The researchers discovered an increase in cerebellar white matter volume in autistic subjects when compared to controls. Other research has found that the cerebral hemispheres can remain enlarged in adults. The frontal, temporal, and parietal lobes appear to be the primary areas of brain enlargement [10]. Magnetic resonance imaging (MRI) is being explored as an alternative diagnostic tool for autism spectrum disorder (ASD), a group of developmental disorders characterized by social communication difficulties and repetitive behaviors [12]. traditionally, ASD has been diagnosed through interview –based procedures ,but brain-based imaging offers detailed information about brain anatomy ,chemistry and function. some studies use MRI to identify brain structure differences between autistic individual and controls [11]. ASD is now categorized into classical autism, Asperger's, pervasive Development Disorder, Childhood Disintegrative Disorder, and Rett's syndrome, each with distinct features and challenges. Rett's syndrome, unique to females, present substantial communication difficulties and limitations in hand use [14].

II. Related work

Recently , convolutional neural networks (CNNs) show impressive performance in the field of pattern recognition ,classification, objective detection, specifically in the field of diagnosing Autism disorder [12]. Summary of related studies on ASD classification using sMRI data is presented in Table 1.

In the work proposed by Mathew j .Leming et al**.** [13] present a method for calculating symmetric similarity matrices from regional histograms of grey matter volumes obtained by T1-weighted MRIs. used fMRI connectivity matrices and univariate estimations of grey matter volumes to compare this method to similar classifications of the same people. Models had AUROCs of 0.7298 (69.71% accuracy) when classifying by only structural similarity, 0.6964 (67.72% accuracy) when classifying by only functional connectivity, and 0.7037 (66.43% accuracy) when classifying b grey matter volumes.

In jingjing Gaw et al. [14] In this study, suggested a new framework for classifying ASD patients using sMRI data from the ABIDE consortium by integrating the convolutional neural network (CNN) and individual structural covariance network. Furthermore, gradient-weighted class activation mapping (Grad-CAM) was used to characterise the weight of features that contributed to classification. The experimental results achieving a high classification accuracy of 71.8% across multiple locations.

In Tanu Wadhera et al. [15] This study has worked on enhancing the binary-classification accuracy of Autism Spectrum Disorder (ASD) persons by separating ASD from Typically Developing (TD) individuals. A hybrid model concatenating VGGNet and ResNet-152 is presented to combine the most discriminating heterogeneous features from both networks to generate a strong feature vector with high classification accuracy. which exhibited an improvement over state-of-the-art classifiers in terms of accuracy (88.12%), sensitivity (91.32%), specificity (86.34%), and ROC (0.88) in categorising ASD and TD people.

In hossien shahamat et al. [16] A 3D-CNN model was suggested in this research to classify brain MRI data into preset groups. Furthermore, a GABM method was developed as a visualisation methodology that provides insights into the classifier's function. To begin, a series of preprocessed MRI scans was used to train the proposed 3D-CNN. The experimental results reveal a 5-fold classification accuracy of 0.70.

In palwinder kaur et al. [17] By integrating neuroimaging methods like structural and functional magnetic resonance imaging (sMRI and fMRI) with machine learning and deep learning approaches, we assessed the performance of a compact CNN model for classifying Autism Spectrum Disorder (ASD). The results showcased an outstanding accuracy, precision, and F1-score, reaching 99.92%, 99.93%, and 99.92%, respectively.

In xiang Guo et al. [2] Based on routinely used MRI sequences, the data presented in this context suggests the feasibility of distinguishing between children with ASD and TD controls. Furthermore, we showcased the effectiveness of employing CNN models rooted in the ResNet-18 architecture for achieving robust detection. Specifically, among the various SSMs, those based on FLAIR or ADC sequences outperformed the others, exhibiting superior AUC values of 0.845 and 0.850, as well as higher accuracy (75.6% and 77.8%), sensitivity (80.0% and 75.0%), and specificity (72.0% and 80.0%) in the independent test dataset.

In Mayank Mishra [18] this paper describes a sMRI-based classification framework for ASD identification that employs an optimizer-based ensemble of Deep Convolution Neural Network (DCNN) with an on-the-fly data augmentation technique. The suggested ensemble model of DCNN with Adam and Nadam optimizer achieved accuracy of 77.58%, 77.66%, and 81.35% on data division ratios of 70:30, 80:20, and 90:10.

In Sakib Mostafa et al. [19] this paper shows The structural MRI images were examined, and a classification model based on convolutional autoencoders (CAE) was proposed. This study employs T1-weighted MRI images Using the proposed CAE-based diagnosis technique, and achieved 96.6% classification accuracy.

In Jovan krajevski et al. [20] they investigate structural and resting state functional MRI (rs-fMRI) for ASD classification using the ABIDE II dataset and several standard machine learning (ML) models and convolutional neural networks (CNNs) in this research. The results reveal that the proposed methods achieve state-of-the-art results with 71.4% accuracy (functional) and 73.4% AUC (structural).

Table 1: Summary of related studies on ASD classification using sMRI data.

Authors	Algorithm	Image	Accuracy
Matthew j .leming	CNN	SMRI	69.71%
Jinging	CNN	SMRI (gradient weighted)	71.8%
Tanu Wadhera	CNN	Neuroimaging	88.2%
Hossien shahamat	3D-CNN	MRI	70%
Plawinder kaur	CNN	SMRI	99%
Xiang guo	DSM single sequence model	CMRI	85%
Mayank Mishra	DCNN	SMRI	81.35%
Sakib Mostafa	CAE	T1 weighted MRI	96.6%
Jovan krajeveski	2D-CNN	SMRI	67%

III. Materials

The benchmark dataset used from open access link to validate our method.as shown in table to the description of the dataset.

Table 2 : Dataset Description.(21)

Intiative	**source**
Datasets	248 datasets (124 with ASD,124 TD controls)
Age range Contribution provided	4 to 7 years Researchers now have a valuable resource to research brain activity and structure in people with ASD and TD.
Kind of image	The dataset has a 8-bit grayscale image in PNG format

IV. Methodology

Convolutional Neural Network (CNN)

CNN is a neural network that is commonly used for image processing, natural language processing, and identifying videos, objects, and voices. CNN's architectural design is divided into several levels, each with its own capability for analyzing images and detecting important information [22].The layers are built in such a way that the convolution layer and the pooling layer alternate, with the final layer being either a global pooling layer or a fully connected layer [23].The layers present in the CNN as shown in the figure 1.

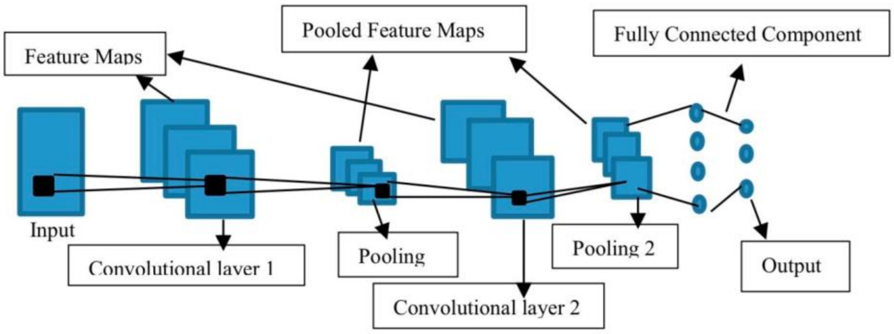

Figure1: The basic structure of a CNN [29].

The Proposed Pre-trained CNN Models

The proposed models is composed of seven pretrained CNN networks: ResNet50, ResNet50V2, VGG16 MobileNet, Inception, Xception, and NasNetMobile. ResNet-50 contains 49 convolution layers, 1 max pooling layer, 1 average pooling layer and 1 fully connected layer (see figure 2)(25). ResNet50V2 contains 50 convolution layers, 3 max pooling layers, 1 average pooling layer and 1 fully connected layer. VGG16 contains 13 convolution layers, 5 max pooling layers, no average pooling layer and 3 fully connected layers (26). MobileNet contains from 20 t0 30 depth-wise separable convolution layers, from 2 to 3 max pooling layers, 1 average pooling layer and ends with linear layer to produce the final classification logits. Inception contains 27 convolution layers, from 2 to 3 max pooling layers, 1 average pooling layer and 1 or more fully connected layers (24) . Xception contains from 36 to 71 depth-wise separable convolution layers, from 2 to 3 max pooling layers, 1 average pooling layer and ends with linear layer to produce the final classification logits. NasNetMobile contains from 20 to 40 convolution layers, from max pooling layers, average pooling layer and. figure 2 and table 3 shows the architecture of the highest model accuracy.

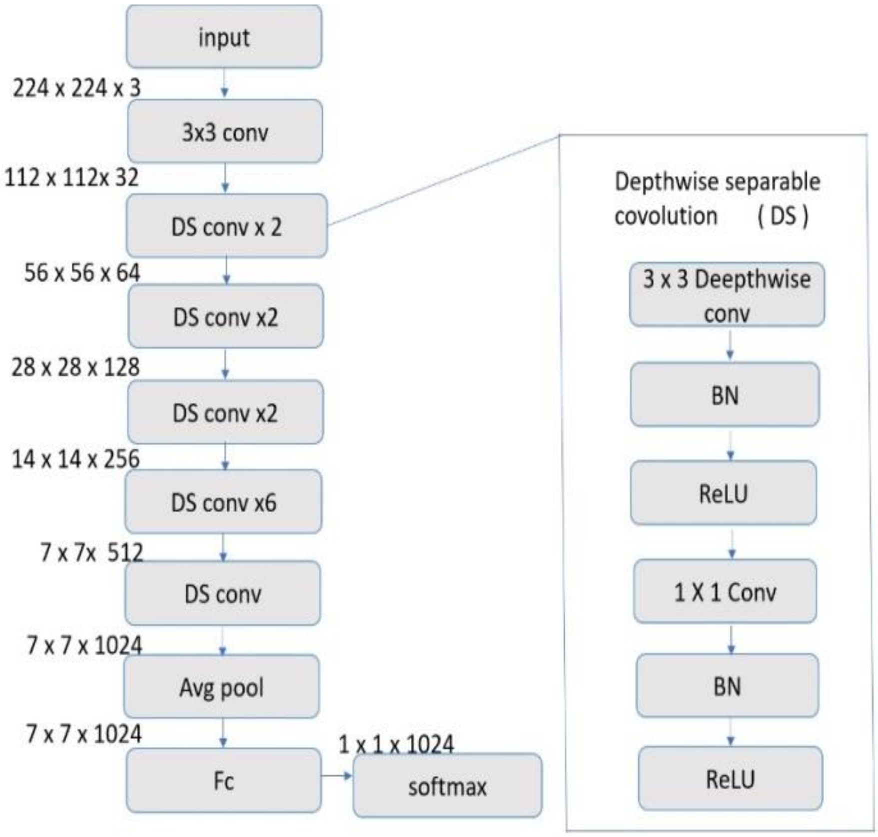

Figure 2: MobileNet architecture

Table(3) Architectural details of the MobileNet mode (24)

Convolution type/strides	Size of filter	Shape of input
Con/s-2	(3 × 3 × 3 × 32)	(224 × 224 × 3)
Con d-w/s-1	(3 × 3 × 32) d-w	(112 ×112 × 32)
Con/s-1	(1 × 1 × 32 × 64)	(112 ×112 × 32)
Con d-w/s-2	(3 × 3 × 64) d-w	(112 ×112 × 64)
Con/s-1	(1 × 1 × 64 ×128)	(56 × 56 × 64)
Con d-w/s-1	(3 × 3 ×128) d-w	(56 × 56 ×128)
Con/s-1	(1 × 1 × 128 ×128)	(56 × 56 ×128)
Con d-w/s-2	(3 × 3 ×128) d-w	(56 × 56 ×128)
Con/s-1	(1 × 1 × 128 × 256)	(28 × 28 ×128)
Con d-w/s-1	(3 × 3 × 256) d-w	(28 × 28 × 256)
Con/s-1	(1 × 1 × 256 × 256)	(28 × 28 × 256)
Con d-w/s-2	(3 × 3 × 256) d-w	(28 × 28 × 256)
Con/s-1	(1 × 1 × 256 × 512)	(14 ×14 × 256)
5 × Conv d-w/s-1	(3 × 3 × 512) d-w	(14 ×14 × 512)
Conv/s-1	(1 × 1 × 512 × 512)	(14 ×14 × 512)
Con d-w/s-2	(3 × 3 × 512) d-w	(14 ×14 × 512)
Con/s-1	(1 × 1 × 512 ×1024)	(7 × 7 × 512)
Con d-w/s-2	(3 × 3 ×1024) d-w	(7 × 7 ×1024)
Con/s-1	(1 × 1 × 1024 ×1024)	(7 × 7 ×1024)
Avg pool/s-1	Pool (7 × 7)	(7 × 7 ×1024)
FC/s-1	(1024 ×1000)	(1 × 1 × 1024)
SoftMax/s-1	Classifier	(1 × 1 × 1000)

Transfer Learning (TL)

Transfer learning has gained significant popularity in recent years within the realm of deep learning due to its ability to efficiently train deep neural networks with limited input data. This technique involves repurposing a pre-trained model, originally trained on specific data, for use with entirely new and distinct datasets. Utilizing transfer learning greatly reduces the training time required for neural networks [27]. In this process, a substantial amount of knowledge from the previous model is transferred to the new one, with the nature of this knowledge depending on the underlying data and problem at hand. Some of the most commonly employed pre-trained models in transfer learning include VGG net, Resnet, inception net, Mobilenet etc. The new dataset can be used to fine-tune the pre-trained CNN. Consider how comparable the new dataset is to the original dataset used for pre-training [28]. Because the new dataset is similar, the same weights can be used to extract features from it.To avoid overfitting, train only the final layers of the network if the new dataset is relatively small. All other levels should remain unchanged. As a result, the final layers of the pre-trained network should be removed. Create new layers. Only the new layers should be retrained.

Training and Testing Model

The whole dataset has been splited into two parts i.e., one part is training the dataset and the other one is testing dataset with a ratio of 90:10. During the model training phase, the redesigned architecture is trained using the ABIDE dataset, which contains MRI images of both autistic and non-autistic individuals. **The Adam optimizer**, an adaptive learning rate optimization technique noted for its success in deep learning applications, is used during the training procedure[1].the learning rate here is 0.0001 with 32 batch size ,image size 224*224*3 with 100 and 400 during training.

V. Proposed Framework and Research Methodology

This section provides a comprehensive overview of the technology and procedures employed during the experiment. The block diagram of the proposed framework is shown in figure 2. The process starts with data preparation for testing and training purposes. Preprocessing operations, including augmentation and resizing, are applied to the dataset. Subsequently, the data is split into testing and training sets, following a ratio of 90:10. The experiment utilizes seven different models of CNN transfer learning. Each CNN model is subjected to fine-tuning of layers and hyperparameters. Finally, the images are accurately classified into two categories: autistic and normal. The evaluation metrics consist of accuracy, loss curves, and precision values to assess the model's performance effectively. figure 3 shows the flowchart of proposed framework

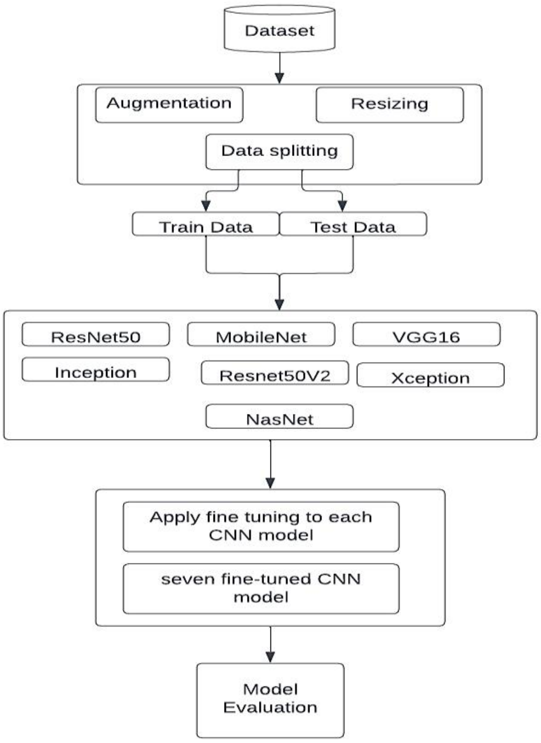

Figure 3: The flowchart of the proposed framework

Environmental Requirements

A graphical processing unit **(GPU)** is required to process images and handle deep learning operations since several mathematical calculations can be executed in parallel. Because GPU installation is an expensive operation that necessitates additional hardware support, we employed a cloud-based service called **Google Colab** in our experiment. Google Colab provides GPU based cloud computing. All of the necessary libraries for performing deep learning operations, such as Keras, TensorFlow, pandas, seaborn, and so on, are implicitly installed within this environment. Colab includes a Tesla K80 GPU with 12 GB of memory and 358 GB of disc space [22].

VI. Experimental Dataset.

The experiment carried out in this investigation necessitates a dataset comprising of MRI images of both autistic and non-autistic youngsters. The dataset consists of structural MRI (SMRI) of T1 weighted images obtained from ABIDE of 248 subjects .in this dataset there is a male gender majority. there were 124 ASD patients and 124 healthy control subjects. which are divided into training and test datasets. Figure 4 shows a sample of the total dataset partitioning

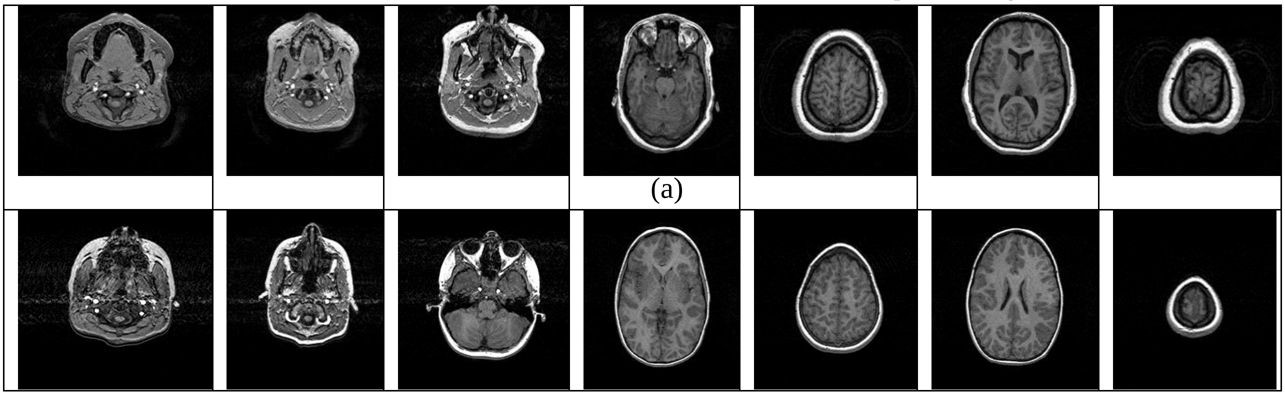

Figure 4: A sample of the dataset for sMRI images used (a) normal. (b) autistic.

Data Augmentation.

Because feature extraction tasks are performed directly from images, the deep learning algorithm does not require explicitly extracting too many features. CNN models used required a 224*224 input picture. As a result, at the start of our experiment, all photos are downsized to 224*224. Rescaling. Some augmentation techniques are used to increase the number of training images. This is accomplished by the use of augmentation operations like the rotation range, shift range, shear, horizontal, vertical flip and zoom. Some parameters have been tweaked to improve performance.

Performance Measures

There are numerous methods for assessing machine learning and deep learning models[29]. For performance evaluation, we used a confusion matrix . The confusion matrix depicts the outcome of the model's prediction considering four scenarios. True positive (TP), false positive (FP), true negative (TN), and false negative (FN) are the four scenarios. Deep learning models are evaluated using metrics such as accuracy, precision, and recall[21].

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

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

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

$$\text{SEN} = \frac{no.of\ true\ positive\ assesments}{no.of\ positive\ assesments} \quad (4)$$

$$\text{SPE} = \frac{no.of\ true\ negative\ assesments}{no.of\ negative\ assesments} \quad (5)$$

VII. Results

The experiment was done out with the use of an autism dataset . The dataset is divided into two categories: autistic and non-autistic images, which depict the image brain of autistic and non-autistic youngsters. To train and evaluate the ASD/TD classifiers, we separated all of the described data into two datasets: testing and training, with a 90:10 ratio have been applied by using colaboratory . Preprocessing was conducted using Keras, and the evaluation of the CNN transfer learning models was performed using Python. During testing, the seven models were assessed with the 'Adam' optimizer, which yielded favorable performance results. Consequently, 'Adam' was selected as the fixed optimizer with a learning rate set at 0.0001. The initial training phase for all seven models consisted of 10 epochs, followed by a subsequent run of 100 epochs.

Table (4) Experiment 1: Comparison of different CNN models using ‘Adam’ optimizer

Model	Accuracy	Precision	AUC	Recall	Sensitivity	Specificity	No.of Parameters
ResNet50	0.8750	0.9477	0.9708	0.9477	0.9738	0.9748	30,010,434
MobileNet	1.00	0.988	0.999	0.988	1.00	1.00	4,253,864
Inception	0.998	0.998	0.999	0.998	1.00	1.00	21,802,784
VGG16	1.00	0.993	0.994	0.993	1.00	1.00	16,320,514
ResNet50V2	0.998	0.998	0.999	0.997	1.00	1.00	23,564,800
Xception	0.997	0.997	0.999	0.998	1.00	1.00	20,861,480
NasNet mobile	0.9583	0.9883	0.999	0.9883	1.00	1.00	4,269,716

Table (5): Experiment 2 Comparison between 7 models by using RMSprop optimizer

Model	Accuracy	Precision	Auc	Recall	sensitivity	Specificty	Loss
ResNet50	0.7917	0.9329	0.9883	0.9391	1.00	1.00	0.4073
MobileNet	0.992	0.992	0.993	0.992	1.00	1.00	0.0063
Inception	1.00	0.9985	0.999	0.9984	1.00	1.00	0.0256
VGG16	0.9583	0.9583	0.9982	0.9583	1.00	1.00	0.0821
ResNet50v2	0.993	0.993	0.995	0.993	1.00	1.00	1.6093e-05
Xception	0.9167	0.9200	0.993	0.9583	1.00	1.00	0.1278
NasNet mobile	0.9167	0.9743	0.9940	0.9743	0.9963	0.9963	0.2089

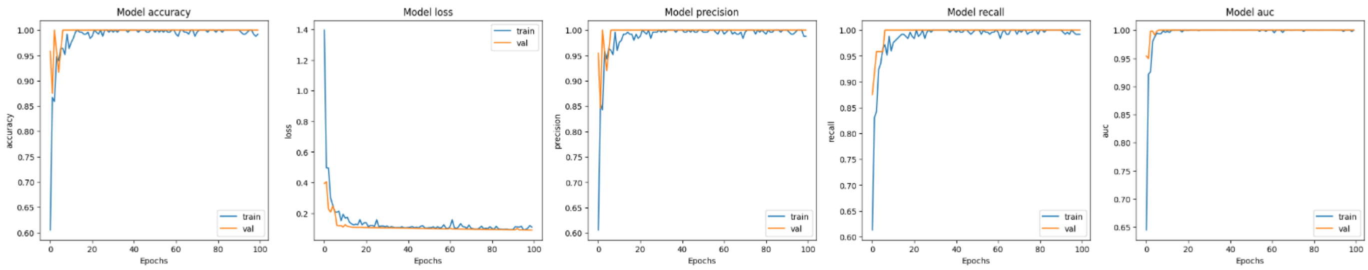

Figure 6: The model curves of accuracy over epoches , precision recall and auc loss in this experiment

In this experiment, the best results were obtained in two models (ResNet50v2 and MobileNet) when compared to the other models tested

Table (6) Experiment 3: Comparison between 7 models using 'SGD' optimizer

Model	Accuracy	Precision	AUC	Recall	Sensitivity	Specificity	Loss
ResNet50	0.7917	0.7917	0.8819	0.7916	0.9583	0.95833	0.4337
MobileNet	0.998	0.998	0.998	0.998	0.999	0.999	0.1288
Inception	0.9583	0.95333	0.9982	0.9583	1.00	1.00	0.1927
VGG16	0.8333	0.833	0.8524	0.833	0.916	0.9166	0.7134
Resnet50v2	0.9582	0.9582	0.9982	0.9582	1.00	1.00	0.1752
Xception	0.7083	0.666	0.671	0.665	0.583	0.666	0.6785
NasNet mobile	0.8333	0.833	0.947	0.8333	1.00	1.00	0.3491

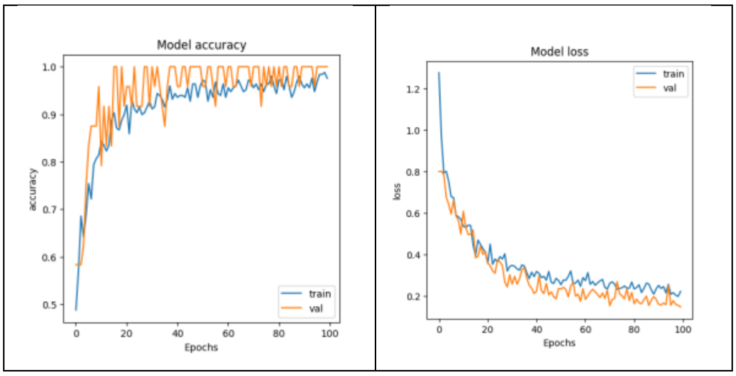

Figure 7: Accuracy and loss over epoches in MobileNet model

VIII.Discussion

According to the results of a comparison of seven alternative models, the MobileNet model provides the best overall outcomes. Deep learning advancements have resulted in the development and testing of advanced models for ASD identification. As a result, we developed a flexible framework based on CNN architecture and the seven models. The recognition of autism using brain (SMRI, T1 weighted images) was implemented in this article to alleviate the disability to diagnose autism at an early age. For recognizing autistic and control images, a Convolutional Neural Network model with pre-trained seven models and transfer learning technique with fine tuning was utilized. The experiment's efficiency was measured using accuracy, precision, recall, AUC, and loss matrices. The MobileNet model, which uses the Transfer Learning approach to accelerate learning, achieved the greatest recognition accuracy of 0.992. Results using Adam optimizer are summarized in Table 2, results using RMSprop optimizer summarized in Table 3, and results using SGD optimizer with 100 epochs summarized in Table 4.

IX.Conclusion

ASD offers numerous obstacles for clinicians and researchers working to understand its molecular basis and target it with medications and therapies. According to recent study, ML/DL algorithms and structural brain MRI data can be used to diagnose ASD. While these trials are promising, they have not yielded the expected results in terms of early and precise diagnosis.. The detection of autism utilising sMRI pictures was implemented in this article to pacify the disability and diagnose autism at a young age. For recognising ASD, a Convolutional Neural Network model with pre-trained MobileNet model and ReesNet50 with transfer learning technique was utilised. The experiment's efficiency was measured using accuracy, precision, and recall matrices. The MobileNet model, which uses the Transfer Learning approach to accelerate learning, achieved the highest recognition accuracy of 99%.

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