ISSN 2278-3091
Volume 10, No.1, January - February 2021
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse471012021.pdf
https://doi.org/10.30534/ijatcse/2021/471012021

AutismNet: Recognition of Autism Spectrum Disorder from Facial Expressions using MobileNet Architecture

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ABSTRACT

Autism Spectrum Disorder (ASD) is associated with neuro developmental disorders that deter the development of social interaction and communication abilities. Diagnosis of autism is one of the challenging tasks for researchers and doctors since the diagnosis is based on abnormalities in brain functions that may not flourish until the disorder is fully established. Facial expression analysis can be an effective solution for the diagnosis of autism in an early stage by exploiting a child's expressions using automated systems. This research work aims to recognize autism from facial expressions using a deep learning model. The proposed model was implemented using Convolutional Neural Network (CNN) that is developed by the MobileNet model. The technique transfer learning was also implemented in this research work to amplify the performance of the model. The experimental result showed that the MobileNet model with a transfer learning approach could provide satisfactory results in the recognition task by achieving the highest validation accuracy of 89% and test accuracy of 87%. The F1-score and precision value also advocated the reliability of our recognition of the approach by achieving the highest score of 87% for both metrics.

Key words: Autism, Deep Learning, Convolutional Neural Network (CNN), Transfer Learning, MobileNet.

1. INTRODUCTION

Autism spectrum disorder (ASD) also known as autism is a dysfunction in the neural system which causes difficulties in verbal and non-verbal communications, irregular responsiveness to sensory organs as well as difficulty in social skills. ASD may be characterized by a child's behavioral pattern, such as difficulty in making meaningful movements, lack of name response, poor facial expressions, not saying a single word for 16 months, and many more.Over the last 30 years, the pervasiveness of ASD has an estimation of 1 in 54 infants being affected [20].The cause of ASD is still unknown or, more accurately, no specific marker has yet been identified as such that no medications have yet to be specified. However, it is proven that genetic and environmental factors play a crucial role in the causes of ASD. It has also been found that ASD is influenced by genetic factors [1]. Social skills enhancement, comprehension and analytical skills can be improved by diagnosing ASD as early as possible. As there is no conclusive marker for autism, diagnosis is made on various factors such as genetic testing, diagnosis of the neural system, physical examination, dysmorphic characteristics. As young kids do not develop their speech and cognitive ability earlier than three years, it is difficult to diagnose them for ASD. As such, parents are advised to observe the behavioral patterns and social skills of their infant. MRI, PET, and fMRI are by far the most common screening approaches used to identify autism for neurological disorders. These screening approaches are used to visualize the internal state of the brain. For genetic testing, gene PTEN, MECP2 is used for early stage screening which is responsible for neural functionality. Chromosomal microarrays are advised for all infants as CMA testing detects delayed development of cognitive abilities and intellectual disability [1]. If the infant is still in the neonatal phase, such screening methods would not work. Also grave's diseases and some other precipitate symptoms like autism which makes it difficult to diagnose.

With the recent technological advancement, Artificial intelligence (AI) has become an eminent research field in image analysis and natural language processing, medical imaging, and so on. Evolution machine learning, as well as deep learning approaches, make it possible to analyze images in a more efficient way than the traditional image processing techniques. Deep learning approaches make it possible for machines to learn like humans by utilizing artificial neural networks. Deep learning requires not so much image processing or feature extraction process which reduces computational resources. When it comes to analyzing visual imagery, the deep learning algorithm convolutional neural network (CNN) is proved a powerful algorithm. The concept of transfer learning boosted the performance of CNN models by transferring knowledge from previous tasks. CNN architectures such as MobileNet [2] is being used for the establishment of automated systems for tasks such as medical image analysis, computational linguistics, satellite imagining, visual media, facial expression analysis, and so on [3-5].

In this research work, we have employed the deep learning model for the recognition of autistic children by exploiting facial expressions. We have applied the most lightweight CNN architecture MobileNet for the recognition task. The network architecture is fine-tuned by adding additional layers and the effectiveness of transfer learning techniques will be studied. The contribution of this research is summed up below:

- Propose a deep learning based framework for recognizing autism from facial expressions.
- Accelerating the performance of the proposed model using transfer learning (TL) technique.
- Establish a comparison between the performance of transfer learning and without transfer learning propositions.

2. LITERATURE REVIEW

Facial expressions analysis has been an important research topic in this modern era. To upgrade the algorithm for face detection and emotion recognition, Ali Hussien Mary et al.[6] used neural networks. For face detection, the Viola-Jones algorithm was used, and CNN deep learning was used for recognition. The proposed algorithm was tested using a universal database and personal images. 92.81% of the accuracy rate is achieved by the algorithm. Feng ping and, Zhiwen Liu [7] developed an algorithm for recognizing facial expressions using CNN and LSTM to compensate for the limitation of the traditional approach. Using CIFAR-10, JAFEE, Cohn-Kanade, BU-3DFE, FER2013, and the Oulu-CASIA expression database, the algorithm was tested. 99.3% accuracy on the JAFEE database, 99.6% on the Cohn-Kanade database was obtained by the method applied in this paper.Kuan Li et al. [8] suggested a simplification of CNN by creating new techniques for cropping images such that only useful features are extracted. Analyses were carried on the CK+ and JAFFE databases to verify the hypotheses. Since the photographs had different color channels and contained different races, it was required to crop and fix the faces. Accuracies of 97.38% and 97.18% were obtained on the identification of facial expression on CK+ and JAFFE datasets respectively. To address multi-cultural facial expression analysis Ghulam Ali et al.[9] studied neural networks for the investigation of different facial expressions. The ensemble approach was used for this purpose. The experiment was conducted on a database that contained Japanese, Taiwanese and RadBoud faces, creating multi-cultural facial dataset. Feature extraction was done by approaches such as LBP, PCA and ULBP for representing different features of faces. Integration of NB classifier and Bernoulli distribution were done in this study. The preprocessing phase included cropping, resizing, normalizing, localizing, and sharpening. The experiment reported the highest accuracy of 89.31% in recognizing facial expressions on the Moroccan test database.

Diagnosis of autism requires early stage recognition. So researchers are trying to explore more and more effective methods for the recognition of autism. On the largest dataset of multi-source FMRI, Matthew Leming et al. [10] performed CNN to compensate for the previous studies which were performed on low sample data and black box problem. The datasets were collected from OpenFMRI, ADNI, ABIDE, ABIDE II, NDCT, NDAR, the UK Biobank, and the 1000 Functional Connectomes Projects. To pre-process the data, skull-stripping and motion corrections were implemented. The average autism accuracy was 57.11% based on 300 studied models. To provide an effective diagnosis of ASD Sewani and Kashef [11] combined deep learning and autoencoder. The brain image dataset was collected for the study from the ABIDE database. The proposed algorithm obtained an accuracy of 84.05%. A multimodal modal was proposed by Michelle Tang et al. [12] using two forms of connectomic data generated by fMRI scans. Neuroimaging data from patients had been collected from the ABIDE dataset. For accurate analysis, quality control, data extraction by time series, and function preprocessing were implemented. The suggested model achieved an accuracy of 74% for classification. In an attempt to settle the PG algorithm, F. Ke and R. Yang [13] suggested an ASD model increase RAM precision, convergence, and stability. The proposed model was tested out using data from the ABIDE dataset using New York University Langone Medical Center data. In the AUC model, the proposed PER-RAM algorithm achieved the highest performance rate of 93.7%.

There have been a lot of work using CNN architecture MobileNet. Wei Wang et al. [14] had implemented a modification of the MobileNet by using a dense block to minimize network parameters and increase accuracy. Caltech-101 and Uebingen Animals with Attributes dataset were used for this DenseNet. Accuracy was 96% for all approaches used in the proposed model.Si-Yuan Lu et al.[15] proposed using a MobileNet and feed forward network algorithm to identify images to validate diagnostic decisions. Total of 301 brain MRI images were used for the methods. The precision of the suggested methods varies from 94 to 96 percent.Haihong et al. [16] suggested a new approach by integrating transfer learning and MobileNet to minimize time consumption and manual work required to evaluate welding defect images. GDXray, a public database was used to validate the method. The result of the method was an accuracy rate of 97.69%.

3. PROPOSED FRAMEWORK AND RESEARCH METHODOLOGY

3.1 System Architecture

In this section, an overview of technologies and methodologies that have carried out throughout the experiment will be described. This section demonstrated the overall process depicted in Figure 1. From image acquisition to training and evaluation is presented in the figure. Firstly,dataset is prepared form training/validation and testing. Initially the model will be trained using training and validation dataset. It incorporates some preprocessing steps with augmentation, rescaling and feature extractions. Then the concept of transfer learning will be implemented. Then the model will be evaluated on testing dataset to validate the performance of our approaches.

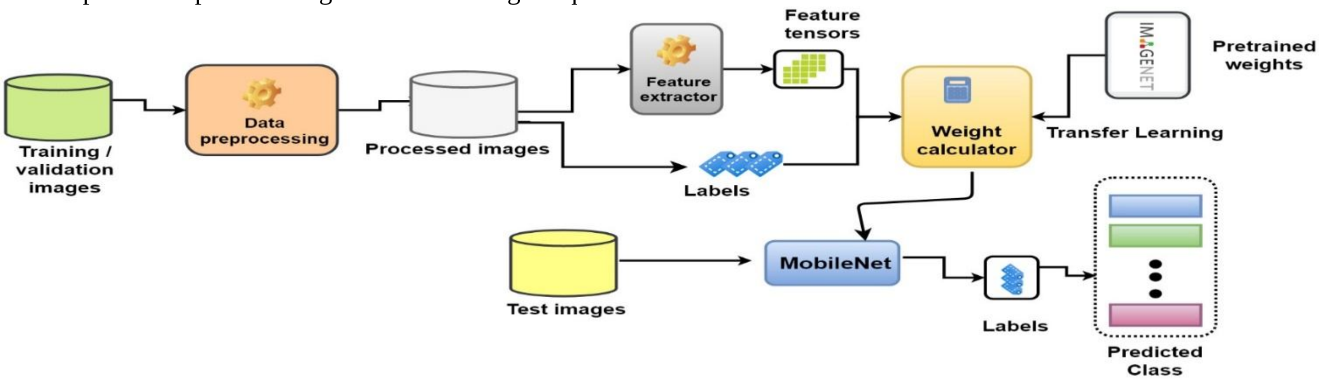


Figure 1: System Architecture (Represents the whole process that is proposed)

3.2Research Methodology

A. Convolutional Neural Network (CNN

CNN is a neural network that is mostly used for image processing as well as NLP and detecting videos, objects, and voices [17]. CNN's architectural pattern is split into numerous layers in which each layer has its functionality for processing the image and discovering useful features. The layers are designed in a way that rotates between the convolution layer and the pooling layer, and the final layer is either a global pooling layer or a fully connected layer.

Convolution Layer: Neurons are the essence of a convolution layer. The convolution layer divides the images into receptive fields, which is a method of splitting the image into small pieces and extracting the patterns of the object. These small pieces of images are calculated by a unique array of weights set according to the need of the analysis. The functional representation of convolution layer can be expressed using equation 1.

$$f_l^k(p,q) = \sum_c \sum_{x,y} i_c(x,y).e_l^k(u,v) \quad (1)$$

$f_l^k(p,q)$ Corresponds to the pth row and qth column of the feature matrix, $i_c(x,y)$ where x, y is the element of the image in cth channel and $e_l^k(u,v)$ represents the kth kernel of lthlayer of (u,v)element.

Pooling Layer: The pooling layer conducts operations to gather related results from the surrounding receptive field and provides the optimum response. By eliminating redundant variants and making the target scope more succinct, the pooling operation sizes down the input field. Mathematical representation is given in equation 2.

$$Z_l^k = g_p(F_l^k) \quad (2)$$

Z_l^k Represents the result of the feature-map of F_l^k in lth layerkth input. g_p Defines the type of operation for the feature-map.

Activation Function: Activation function operates as a defining factor in decision making of identifying patterns which helps speed up the learning process. The mathematical representation is given in equation 3.

$$T_l^k = g_a(F_l^k) \quad (3)$$

g_a Is the type of activation function assigned to the output of convolution F_l^k for lth layer kth input where their result returns an output T_l^k .The types of activation functions that can be allocated to g_a are ReLU, sigmoid, SWISH, tanh and many more.

Batch Normalization: Batch normalization is the method of shifting the hidden values of a feature-map. The latent values

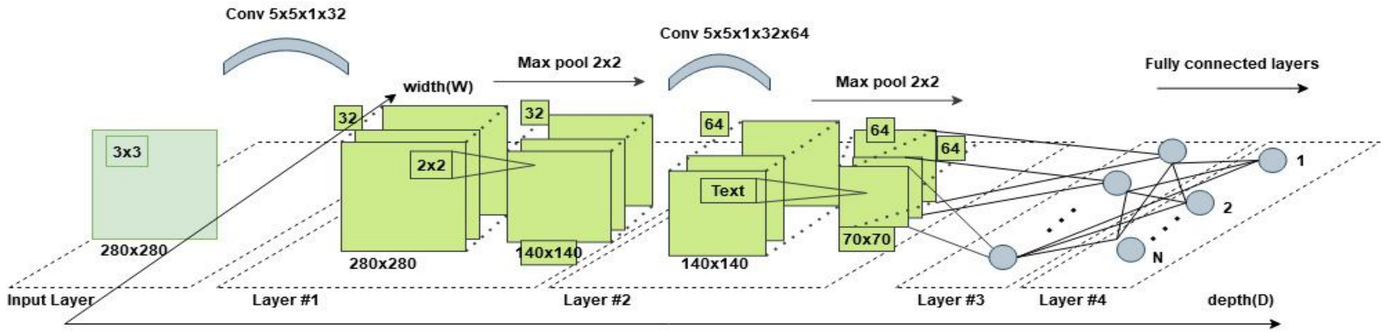
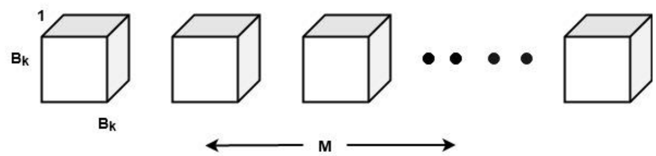


Figure 2: The Convolutional Neural Network

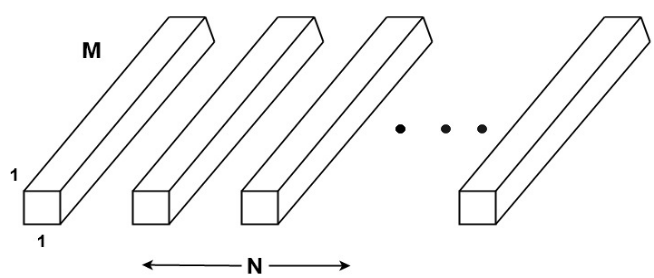
slow down the process of integration and have unexpected effects. In order to achieve accurate results, batch normalization smoothes down the feature-map values. Figure 2 illustrates the architecture on CNN.

B. MobileNet

MobileNet is a model that constructs neural networks suitable for mobiles [2]. This model uses depth-wise convolution architecture to create lightweight, low-complexity models that meet the requirements of mobile architecture. Figure 3 demonstrate the concept of depthwise and pointwise convolution.



(a)



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(b)

Figure 3: Convolution techniques used in MobileNet model, (a) depthwise convolution, (b) Pointwise Convolution

A regular convolutional layer takes F, feature map $D_F \times D_F \times M$ as an input and create G, feature map $D_F \times D_F \times N$. Where D_F and D_G represents the input and output size in feature map, M and N symbolizes input and output channel frequency.

Two layers exist in a depthwise convolution in which depthwise convolution layer is used to add only one filter per input channel and pointwise convolution is used to flatten the result of the depthwise layer. The equation (4) of the depthwise convolution can be written as:

MobileNet model uses depth-wise convolutions that factor the regular convolution into a 1 x 1 convolution known as point-wise convolution. Each input channel uses a single filter and the point-wise convolution merges all outputs. After that the output is separated into two layers, filtering and combing by depthwise convolution.

$$\hat{G}_{k,l,m} = \sum_{i,j} \hat{K}_{i,j,m} . F_{K+i-1, l+j-1, m} \quad (4)$$

$\widehat{K}$ Represents the kernel of the depthwise convolution depicting size $D_K \times D_K \times M$.

The cost of computation in depthwise convolution can be represented by $D_K . D_K . M . D_F . D_F$ .In Table 1 the full architectural details of the MobileNet model in presented [2].

Table 1: Architectural details of the MobileNet model

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)

3.3Transfer Learning (TL)

Transfer Learning as the name implies is a method for transferring knowledge from one task to another [18]. Data needs to be trained in a deep learning model; the transfer learning improves and shortens the process by using already trained data to another model. Figure 4 demonstrate the process of learning.

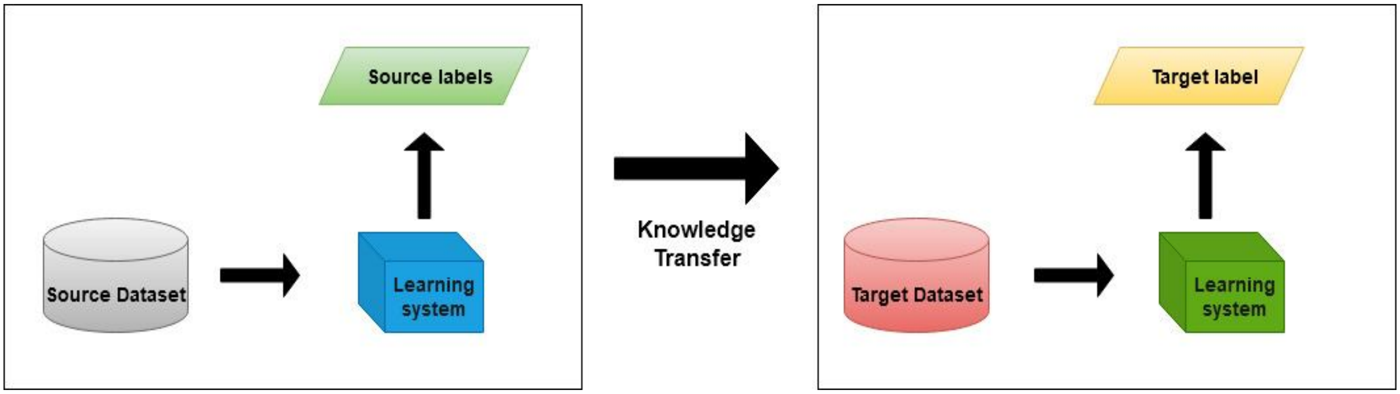

Figure 4: The process of transfer learning

The domain and task must be taken into account for the use of transfer learning. Transfer learning can be used to solve NLP problems, sentiment classification, image classification, and many more. In this research work, weights from pretrained model that was executed on ImageNet dataset was used.

4. EXPERIMENTAL EVALUATION AND RESULT ANALYSIS

4.1Environment Specification

To process images and handle deep learning operations, a graphical processing unit or GPU is needed where multiple mathematical operations can be executed in parallel. Since GPU installation is an expensive process that requires additional hardware support, a cloud-based service called Google Colab is used in our experiment. Google Colab supports GPU which runs on the cloud. All the necessary packages or libraries required for carrying out deep learning operations such as Keras, TensorFlow, pandas, seaborn, etc. are installed implicitly within this environment. Colab comes with a tesla k80 GPU with a memory of 12 GB, and 358 GB of disk space.

4.2Experimental Dataset

The experiment that has been carried out in this experiment requires a dataset consisting of facial expressions of both autistic and non-autistic children. There is no such institutional database. We used a dataset from Kaggle[1] that that contains facial expressions of autistic children. In this repository, there is a total of 3136 images which are split into training, validation, and test dataset. Figure 5 exhibits a glimpse of our dataset and in Table 2 the overall dataset splitting is given.

Table 2: Overall Dataset Splitting

Images	Training images	Validation Images	Test Images
Autistic	1268	250	50
Non-autistic	1268	250	50

(a)

(b)

Figure 5: Dataset used in the experiment, (a) Autistic, (b) Non-autistic

[1]https://www.kaggle.com/gpiosenka/autistic-children-data-set-traintestvalidate

4.3Data Preprocessing and Hyper-parameter Setup

Deep learning algorithm does not require extracting too many features explicitly since features extraction tasks are conducted directly from images. The MobileNet architecture requires input image of shape 224*224. So, at the beginning of our experiment, all images are resized to the size of 224*224. Rescaling. The number of training images are increased using some augmentations techniques. Augmentation operations such as flip, shift, and zoom are performed for this purpose. Some parameters are adjusted for better performance. The adjustments are given in the following Table 3.

Table 3: Hyper-Parameters Setting

Parameters	MobileNet
Batch size	32
Learning rate	0.001
Image size	224*224
Training Epoch	50
Optimizer	RMSprop
Drop block	0.5

4.4Performance Evaluation

There are several approaches for evaluating a machine learning and deep learning models. We have used confusion matrix for performance evaluation [19]. Confusion matrix visualize the outcome of the prediction through the model using four situations. These situations are true positive (TP), false positive (FP), true negative (TN), and false negative (FN). The metrics that are used for evaluating deep learning models are accuracy, precision, recall and F1-score (F1-measure). These metrics are formulated using equations 5, 6, 7, and 8.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (6)$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \quad (7)$$

$$F - measure = \frac{2 \times \operatorname{Re} call \times \Pr ecision}{\operatorname{Re} call + \Pr ecision} \quad (8)$$

4.5Result and Analysis

In this segment the reported results of our approach is demonstrated and analyzed. Firstly we present the class-wise classification performance for MobileNet model while predicting autistic and non-autistic children's in Table 4. Both the cases with and without transfer learning are analyzed. In the following table precision, recall and F1-values are reported for out model.

Table 4: Class-wise classification report for both approaches

Method	Class	Precision (%)	Recall (%)	F1 (%)
MobileNet (With TL)	Autistic	86.27	88.0	87.12
	Non-autistic	87.75	86.0	86.86
MobileNet (Without TL)	Autistic	80.39	82.0	81.0
	Non-autistic	81.62	80.0	81.0

From this presentation it can be observed that the highest precision and recall value is achieved for the model with transfer learning approach. This implies that the proposed model performs in a decent manner while predicting correct outcomes which are positives and true positives. The same result has been observed when comparing with respect to F1-score, which denotes the symphonic average of both precision and recall. Again approach with TL outperforms for both classes.

Table 5 presents the average scores of evaluation metrics Precision, recall and F1-score. It can be clearly seen that, MobileNet model with transfer learning approach outperforms the approach without transfer learning. Highest observed value for all the three metrics is 87% for TL approach, on the other hand without TL approach gained score of 87% for all metrics.

Table 5: Average classification report

Model	Precision (%)	Recall (%)	F1-score (%)
MobileNet-TL	87.0	87.0	87.0
MobileNet-WTL	81.0	81.0	81.0

In Table 6, accuracy and loss that are observed during the experiment is illustrated. The best validation accuracy is 89.0% which is reported for MobileNet model with TL approach. When the trained model is tested with test dataset, the best test accuracy was observed for TL approach which is 87%. The lowest validation and test loss is also recorded for TL approach.

Table 6: Accuracy and loss for both approaches

Model	Accuracy (%)		Loss	
	Validation	Test	Validation	Test
MobileNet-TL	89.0	87.0	0.15	0.21
MobileNet-WTL	81.25	81.0	0.42	0.55

A more comprehensive representation through confusion matrix is presented in Figure 6 and 7 to give an insight of our proposed approaches in terms of the total number of right and wrong predictions.

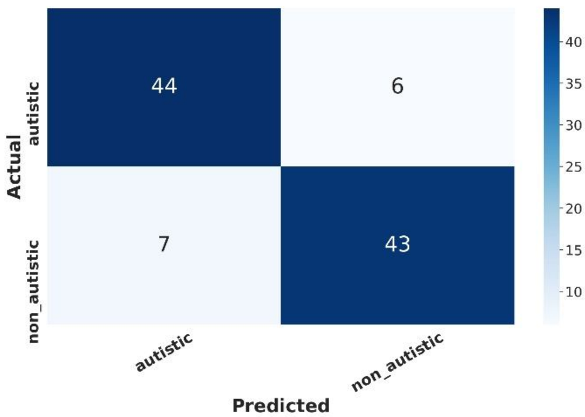

Figure 6: Confusion matrix for MobileNet with transfer learning

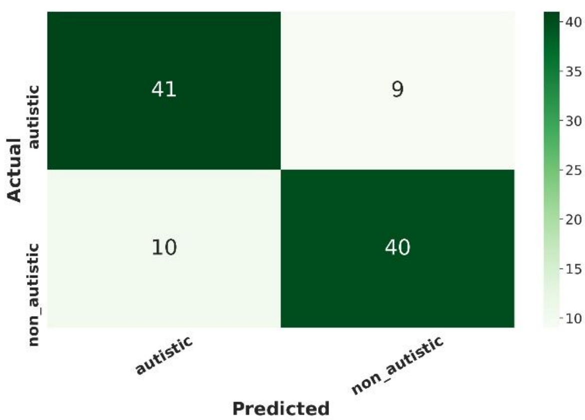

Figure 7: Confusion Matrix for MobileNet without transfer learning

From figure 6 it can be seen that, MobileNet model with TL approach correctly predicts 44 autistic cases and 43 non-autistic cases. The total number of correct prediction is 87 where only 13 cases was recorded as misclassification. There have been more misclassification cases for without TL approach represented in Figure 7. This approach reported total of 19 misclassifications, implies approach with TL is more efficient in the recognition task.

In Figure 8 the model performance with respect to accuracy over epochs is illustrated. This representation indicates that the MobileNet model with TL approach performs better in facial recognition task while diagnosis autism.

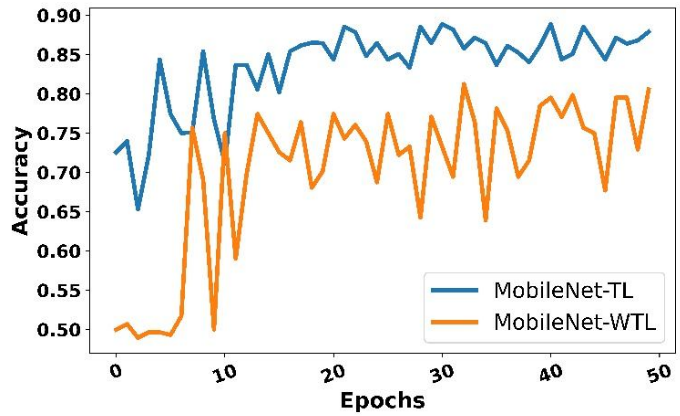

Figure 8: Accuracy over epochs for both approaches

5. CONCLUSION AND FUTURE WORK

In this article, the recognition of autism using facial expression was implemented to pacify the disability to diagnosis autism at an early age. A Convolutional Neural Network model using pre-trained MobileNet model with transfer learning technique was used for recognizing facial expressions. Accuracy, precision, recall, and F-measuring matrices were used to measure the efficiency of the experiment. The MobileNet model with the Transfer Learning technique boosts the learning process showed promising results by achieving the highest recognition accuracy of 87%.

Our work has shown a satisfactory outcome yet has the opportunity for growth. A bigger database size will improve the accuracy of the model. We would also like to perform our experiments on other CNN architectures such as EfficientNet, Inception-V4, Xception, GhostNet, etc. as future research. Implementation of hybrid architecture by integrating various deep learning and machine learning methods may also be an interesting field to venture into.

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REFERENCES

1. H. Hodges, C. Fealko, and N. Soares, “Autism spectrum disorder: definition, epidemiology, causes, and clinical evaluation,” Translational pediatrics, vol. 9, no. Suppl 1, p. S55, 2020.
2. A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “Mobilenets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.
3. F. Zhang, Q. Li, Y. Ren, H. Xu, Y. Song, and S. Liu, “An expression recognition method on robots based on mobilenet v2-ssd,” in 2019 6th International Conference on Systems and Informatics (ICSAI). IEEE, 2019, pp. 118–122.
4. M. Nateghi, “Detection, recognition and tracking cars from uav based implementation of mobilenet-single shot detection deep neural network on the embedded system

by using remote sensing techniques," Journal of Radar and Optical Remote Sensing, vol. 2, no. 4, pp. 49–57, 2020.
5. J. Sivasamy and T. Subashini, "Classification and predictions of lung diseases from chest x-rays using mobilenet," International Journal of Analytical and Experimental Modal Analysis, vol. 1, 2020.
6. A. H. Mary, Z. B. Kadhim, and Z. S. Sharqi, "Face recognition and emotion recognition from facial expression using deep learning neural network," in IOP Conference Series: Materials Science and Engineering, vol. 928, no. 3. IOP Publishing, 2020, p. 032061.
7. F. An and Z. Liu, "Facial expression recognition algorithm based on parameter adaptive initialization of cnn and lstm," The Visual Computer, vol. 36, no. 3, pp. 483–498, 2020.
8. K. Li, Y. Jin, M. W. Akram, R. Han, and J. Chen, "Facial expression recognition with convolutional neural networks via a new face cropping and rotation strategy," The Visual Computer, vol. 36, no. 2, pp. 391–404, 2020.
9. G. Ali, A. Ali, F. Ali, U. Draz, F. Majeed, S. Yasin, T. Ali, and N. Haider, "Artificial neural network based ensemble approach for multicultural facial expressions analysis," Ieee Access, vol. 8, pp. 134 950–134 963, 2020.
10. M. Leming, J. M. Górriz, and J. Suckling, "Ensemble deep learning on large, mixed-site fmri datasets in autism and other tasks," arXiv preprint arXiv: 2002.07874, 2020.
11. H. Sewani and R. Kashef, "An autoencoder-based deep learning classifier for efficient diagnosis of autism," Children, vol. 7, no. 10, p. 182, 2020.
12. M. Tang, P. Kumar, H. Chen, and A. Shrivastava, "Deep multimodal learning for the diagnosis of autism spectrum disorder," Journal of Imaging, vol. 6, no. 6, p. 47, 2020.
13. F. Ke and R. Yang, "Classification and biomarker exploration of autism spectrum disorders based on recurrent attention model," IEEE Access, vol. 8, pp. 216 298–216 307, 2020.
14. W. Wang, Y. Li, T. Zou et al. "anovelimageclassificationapproach via dense-mobilenet models, mob," Inf. Syst, vol. 2020, pp. 1–8, 2020.
15. S.-Y. Lu, S.-H. Wang, and Y.-D. Zhang, "A classification method for brain mri via mobilenet and feedforward network with random weights," Pattern Recognition Letters, vol. 140, pp. 252–260, 2020.
16. H. Pan, Z. Pang, Y. Wang, Y. Wang, and L. Chen, "A new image recognition and classification method combining transfer learning algorithm and mobilenet model for welding defects," IEEE Access, vol. 8, pp. 119 951–119 960, 2020.
17. S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in 2017 International Conference on Engineering and Technology (ICET). Ieee, 2017, pp. 1–6.
18. U.Côté-Allard, C. L. Fall, A. Drouin, A. Campeau-Lecours, C. Gosselin, K. Glette, F. Laviolette, and B. Gosselin, "Deep learning for electromyographic hand gesture signal classification using transfer learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 760–771, 2019.
19. Marom, N.D., Rokach, L., Shmilovici, A., 2010. Using the confusion matrix for improving ensemble classifiers, 2010 IEEE 26th Convention of Electrical and Electronics Engineers in Israel, IEEE. pp.000555–000559
20. McCarty, Patrick, and Richard E. Frye. "Early Detection and Diagnosis of Autism Spectrum Disorder: Why is it so difficult?" Seminars in Pediatric Neurology. WB Saunders, 2020