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EFFICIENT NET-BASED TRANSFER LEARNING TECHNIQUE FOR FACIAL AUTISM DETECTION

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Abstract. Autism Spectrum Disorder is a neurological disorder in which an individual faces life-long effects in communication and interaction with others. Nowadays, the Autism Spectrum disorder ratio is increasing drastically more than ever before. Autism can be identified at all developmental levels as a "behavioural condition," and its symptoms often arise between the ages of two and four. The ASD issue starts during puberty and persists through adolescence and adulthood. Children with ASD use both nonverbal and verbal behaviour to communicate, and they struggle with joint attention and social reciprocity. Children with autism are frequently socially isolated as a result of these problems. Through very expensive and time-consuming screening exams, autism spectrum features can be identified. As one of the possible mirrors of the brain, children's faces can be utilised as a biomarker and as a quick and convenient technique for the early identification of ASD. An effective, genuine, and automatic method of face-based spectrum disorder identification is required. In this study we compare the transfer learning approach used for autism identification with the convolutional neural network (CNN)-based efficient-net strategy to identify autistic children using facial images. We used an open-source Kaggle dataset and evaluated the model performance in terms of accuracy, confusion matrix, precision, recall, and F1 measure. Efficient shows an accuracy of 97% on the benchmark dataset and beats the baseline technique of transfer learning-based approaches. This study can be used to help medical professionals validate their initial screening procedures for finding youngsters with ASD disease.

Key words: Autism spectrum disorder, Convolutional Neural Network (CNN), Transfer Learning, EfficientNet, Facial Images

1. Introduction. Autism Spectrum Disorders (ASD) are rapidly increasing in all age groups of the population today. However, it is the most alarming developmental disorder that disrupts children's social skills, communication skills, and imagination. Children with autism have problems with repetitive behaviour patterns, anxiety, self-harm, abnormal sleep patterns, behaviour-altering aggression, and attention deficits. Autism symptoms vary in children from mild to severe. An early diagnosis and detection can help treat this autistic problem. The medical team, with the help of parents and guardians, manages the ASD screening instruments, which are the assessments used to identify autism spectrum disorder. Despite deep research, the ASD neural mechanism problem is still unclear. Generally, ASD diagnosis is based on behaviour, not on the cause or mechanism [13]. In ASD diagnosis, Genetic tests are widely used to identify genetic causes, however, genetic tests provide only indication about potential risk and not diagnosis information. The researchers are using brain imaging techniques to diagnose ASD [7]. However, imaging-based techniques have some limitations in terms of datasets. Researchers are investigating machine learning methods to evaluate ASD swiftly and economically [28]. Machine learning-based solutions offer quick, accurate, and automatic procedures for ASD detection. Machine learning, a branch of artificial intelligence, has the potential to improve neurological disease identification using computer approaches [24, 14]. There are different ways to detect ASD based on different modalities of neuroimaging data like Electroencephalography (EEG), Magnetoencephalography (MEG), Electrocorticography (ECoG), Magnetic resonance imaging (MRI) and Functional near-infrared spectroscopy (fNIRS) [9].

1.1. Motivation. ASD (ASD) is a condition marked by social difficulties. In accordance with the social motivation theory, ASD causes a decline in social motivation because affected individuals find social stimuli less satisfying than neurotypical individuals. The social motivation hypothesis offers a developmental perspective on how social deficiencies in ASD may later manifest as faulty reward processing. According to social theory, young ASD patients pay less attention from an early age to social cues like faces and gaze direction. Due to the lack of possibilities for social learning (such as friendships, cooperative play, and joint attention), the growth

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of social skills is hampered as a result. The social motivation theory identifies impaired social approach and involvement as two crucial diagnostic features of ASD. However, these mentioned procedures are expensive and are out of reach treatment, especially in developing countries. Late diagnosis and identification ASD is commonly due to:

- The identification of ASD children near the age of two is done through interactive sessions that call for clinical professionals [23].
- The lack of availability of the appropriate physicians, especially in underdeveloped countries [27].
- The people who are not aware of the ASD disorder do not take this disease as seriously as they should at an early stage.
- Additionally, due to the high expenses of the sophisticated equipment and qualified staff needed for these tests, Children from racial and ethnic minorities who get a primary screening are less likely to undergo further medical exams [30].

It is clear from the above discussion that the current developments in the field of deep learning, particularly convolutional neural networks, we can rely on automatic feature extraction. We proposed simple and lightweight models that provide better results than transfer learning-based techniques. Researchers are investigating and creating novel diagnostic methods for the early detection of ASD based on facial expression as a new area of study. The distinctive characteristics of an ASD person makes them easier to recognize from facial expressions. According to studies conducted at the University of Missouri, children who have autism tend to have particular facial characteristics, such as a big upper face and wide-set eyes. Compared to children without the condition, their faces frequently have a shorter centre section, encompassing the cheeks and nose [3]

- Our proposed technique provides better results with simple models.
- The proposed technique beat the state of art transfer learning techniques and we make comparisons to prove the effectiveness of our technique.

The remaining part of paper is organized in sections. Section 2 is about the state of art literature review, section 3 is about proposed methodology. In section 4 we discuss about performance metrics and results and the final section, section 5, is about conclusion and future work.

2. Literature Review. The autism condition is associated with brain development issues affecting how individuals interact and communicate. Marotta et al. [18] define autism as ”Complex neurobehavioral and neurodevelopmental conditions characterized by altered sensory processing, restrained and repetitive patterns of behaviour or interests, and impaired social interaction and communication.” Children affected by autism often portray limited and monotonous patterns of conduct. The disorder is not easily diagnosed because it affects people differently, making it hard to distinguish the unique features that characterise the condition. The term ‘spectrum’ depicts the wide range of signs and symptoms that affect patients with varying severity. Autism spectrum disorder is often detected during early childhood and impacts how people function in society. For instance, some people are easily irritated and have difficulty maintaining relationships, while others suffer from attention deficit, affecting their education adversely. It is impossible to ascertain the causes of autism disease though some cases are associated with genetic inheritance, preterm births, or head injuries at a young age. Khodatars et al. [15] argue that autism can be diagnosed using numerous diagnostic protocols, especially after children mark their third birthday. The ailment cannot be cured, but early diagnosis, treatment, and intensive management help improve the lives of the affected individuals. Hence, autism is a lifelong-manageable condition though its prevalence over the last decade raises global concern.

Over the last decade, the cases of autism spectrum disorder have increased at a concerning rate. Chiarotti et al.[8] state autism spectrum disorder (ASD) frequency has significantly increased over the past few decades, leading to allegations that autism is an ”epidemic.” The cases reported in different regions indicate that the incidents diagnosed are increasing. However, some may argue that the diagnosis procedures have improved over the years with proper recording, unlike in the past. For instance, countries in the global south report more cases than in the past due to enhanced capability to track and diagnose the ailment. Contemporary, approximately one in 54 children is suffering from ASD globally. The condition is more prevalent among boys than in girls at the rate of 3.68% and 1.25%, respectively. The cases might still be more than the current studies report since some parents do not like to disclose their children’s struggles due to fear of stigmatisation. Botha et al.[6] states that the media and some societies frame autism negatively and stereotype autism in a way that encourages individuals suffering from the condition to conceal or camouflage as non-autistic even when it impacts their functioning and wellness. In the US, autism affects about 2% of all children, creating a heavy financial burden on taxpayers as the affected children need significant medical, educational, and social support. As a result, the growing number of ASD cases discovered using various diagnostic techniques affects many individuals and families.

Mottron et al.[21] states that healthcare professionals rely on several diagnostic approaches to identify children with autism where behavioural observation remains critical but artificial intelligence might revolutionise ASD screening and diagnosis. According to this study, ”The planning of intervention and educational services is poorly aided by a single categorical diagnosis, which encompasses such heterogeneity of developmental history, intelligence, comorbidity, and severity.” Physicians do not have one verified diagnostic approach recommended for use but depend on varying ones, complicating the process. A child might be misdiagnosed as autistic due to less severe symptoms associated with autism, while others fail to be identified until later. McCarty at al.[19] defined ASD, categorised, and diagnosed per the criteria established by DSM-5, though the manual does not provide a formal test as with other disorders. Therefore, most medics depend on behavioural measurements to evaluate suspected cases.

Learning based approach have great contribution in the prediction of autism disease [5],[29]. Parisot et al.[25] built a population graph using a graph-based technique and trained a graph convolution network (GCN) to do so. On the ABIDE1 dataset, they attained a classification accuracy of 70.4%. Haque et al.[10] developed ”deep convolutional neural network” deep learning methodologies, which drew inspiration from the VGGNet network family. Utilising the well-known FER2013 dataset [2], a Deep Convolutional Neural Network (DCNN) algorithm was trained. The brightness of the images in this dataset has been altered to test the model’s performance in various lighting scenarios and to recognize the expressions on the faces of children with autism. Li et al. [17] used an end-to-end learning-based strategy for identifying autism spectrum disorder (ASD) using facial data such as expressions, action units, arousal, and valence. This study uses convolutional neural network representations of several facial traits that have been trained on real-world pictures. The video dataset contains 105 children (62 with autism spectrum disorders and 43 without). Ahmed et al. [3] classified ASD subjects from healthy controls using a support vector machine (SVM) and a limited Restricted Boltzmann Machine (RBM) to extract characteristics from fMRI data. The dataset is initially pre-processed, which includes slice time correction and normalization. This study employed 105 Typical control (TC) and 79 ASD patients from the renowned database ABIDE. The results demonstrate that when classifying ASD using grid-search cross-validation, the proposed framework performs very well. The outcomes also imply that merging RBM and SVM techniques may be employed as an ASD detection tool in the future. Khosla et al.[16] used transfer learning-based model of MobileNet, InceptionV3, and InceptionResNetV2 models, and reported poorer accuracy compared to other studies. They also used the MD5 hash technique to remove duplicates from the dataset. Mishra et al.[20] exploited surface morphometric properties of T1-weighted structural magnetic resonance imaging (sMRI) to develop a machine-learning approach for the detection of ASD. The proposed study integrates classification evaluation of the used machine learning models based on the surface morphometric characteristics of the left and right hemispheres of the brain. The Decision Tree (DT) and Random Forest (RF) are employed for categorisation.

Hosseini et al.[11] has good contribution in identification of autism and used CNN-based architecture MobileNet as transfer learning technique. The proposed method has a good accuracy result on images of small children. The visual features were extracted using the pre-trained deep learning models, which used three fully linked layers topped by a dense layer to forecast. Rahman et al.[22] used CNN-based architecture XceptionNet which was utilised to identify the autistic disease. On the facial image dataset for autism identification, Alsaade et al. [4] used three CNN-based architectures: Xception, VGG19, and NASNETMobile, and achieved the maximum accuracy. All the aforementioned CNN-based models, which were intensively trained on the ImageNet dataset, which contains 14 million images divided into 1000 categories, are used to extract attributes from the photographs in the Kaggle autistic image dataset (https://www.kaggle.com/general/123978). Using fMRI scans from the ABIDE-1 dataset, Prased et al.[26] classified Using a multilayer perceptron (MLP) based classification model with autoencoder pretraining, ASD is distinguished from Typically Developing (TD). The suggested method identified the correlations between brain regions that contribute most to the categorization problem

Table 2.1: Summary of Literature Review

Study	**Year**	**Technique**	**Dataset**	**Performance Metrics**
Parisot et al. [25]	2018	Graph convolution network (GCN)	ABIDE and ADNI	Accuracy and AUC
Haque et al. [10]	2018	Deep convolutional neural network (DCNN)	Fer2013	Accuracy Score
Li et al. [17]	2019	Convolution neural network (CNN)	Video dataset	F1 score
Ahmed et al. [3]	2020	Restricted boltzmann machines with SVM	ABIDE-I	Accuracy, ROC curve and F1, precision, recall
Khosla et al. [16]	2121	MobileNet, InceptionV3, and InceptionRestNetV2	Facial Images	Accuracy Score
Mishra et al. [20]	2021	Random Forest and Decision Tree	ABIDE-I	Accuracy, ROC curve and F1, precision, recall
Hosseini et al. [11]	2022	MobileNet	Facial Images	Accuracy score

using the Integrated Gradients (IG) and DeepLIFT approaches. Following regions are shown to be related with this analysis: left lingual gyrus, right insula lobe, right cuneus, right middle frontal gyrus, and left superior temporal gyrus.

3. Proposed Methodology. We divided the methodology portion in to subsection to elaborate the purpose of each section.

3.1. Dataset Description. Dataset Description. In this paper, we use the open-source dataset available on Kaggle [1]. The dataset is divided in to three groups for training, validation, and evaluation with the ratio of 86.38%, 10.22%, and 3.41%, respectively. Training set is used to train the model, validation to check the model, whilst on the test model we validate the effectiveness of proposed technique. The training set has 2536 face images, validation set has 300 and the test set has 100 images. While non-autistic face photographs were haphazardly gathered from the internet, web sources with issues with autism were used to obtain the youngsters with autistic faces. This dataset includes 2D RGB photos of kids between the ages of 2 and 14, with the majority falling between those two and eight. The dataset showed an around 3:1 male to female ratio, compared to a nearly 1:1 ratio for the autistic class and normal control class (Fig. 3.1).

3.2. Pre-processing. The duplicate photographs were removed from the dataset, and the images were cropped to just display the facial portion. We normalise the dataset between 0 and 1 by using standard PyTorch function transforms.

3.3. Feature Extraction and Classification. Thanks to the deep learning algorithms that made possible automatic feature extraction. The effort of extracting features from images is challenging, but with the advent of architecture based on convolutional neural networks, this task has become much easier. To categorize photos of autism, we are using convolutional neural networks, which apply deep learning methods for classification problems. The following layer types make up their layered structure: -

- Max Pooling Layer
- Sub-sampling Layer of the Convolution Layer
- Integrated Connection Layer

We used EfficientNet [31] in this study to detect autism because transfer learning leverages pretrained models from the ImageNet dataset rather than training from scratch. EfficientNet, one of the most efficient CNN models, exhibits exceptional accuracy on both ImageNet and common picture classification tasks using transfer learning while utilising the least number of FLOPS for inference. The EfficientNet B0 model, which is the foundational EfficientNet model, is used in this study with an input image size of (224 X 224 X 3). Dropout layers and batch normalisation can be added to the EfficientNet model during fine-tuning to help with overfitting issues. However, in our case, we just change the last layer of the classifier to make the binary classification task. The overall summary of the proposed model is shown in Fig. 3.2.

3.4. Method of Instruction. On the training dataset, we used batch-trained to the model, and the test dataset served as the model's evaluation. Utilising the fit-generator method, we created a special dataset

Fig. 3.1: Face Images

function for this. The model is then developed and assembled using the training data and predefined hyper-parameters.

3.5. Rate of Learning. To decay, we employ the learning rate. Modern neural networks are trained using the learning rate decay technique, and if there is no change in loss values, the learning rate value is changed. The neural network is first trained with a high learning rate, which is subsequently decayed until local minima are discovered. It has been demonstrated to help with both generalisation and optimization.

3.6. Optimization. One of the key ideas in deep learning is cost function optimization. The gradient descent algorithm is the most popular one. The little dataset in our situation, however, makes it quite slow. We employ a variant of this method called Adam to assist our model in learning far more quickly.

3.7. Loss Function. The suggested study uses the cross-entropy loss function and relies on the binary categorization of images. Finding the differences between two probability distributions is its main goal. We employed the sigmoid function for the activation function.

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=============
EfficientNet (EfficientNet)                 [32, 3, 224, 224]   [32, 2]              --          Par
tial
├─Sequential (features)                     [32, 3, 224, 224]   [32, 1280, 7, 7]     --          Fal
se
│    └─Conv2dNormActivation (0)             [32, 3, 224, 224]   [32, 32, 112, 112]   --          Fal
se
│    │    └─Conv2d (0)                      [32, 3, 224, 224]   [32, 32, 112, 112]   (864)       Fal
se
│    │    └─BatchNorm2d (1)                 [32, 32, 112, 112]  [32, 32, 112, 112]   (64)        Fal
se
│    │    └─SiLU (2)                        [32, 32, 112, 112]  [32, 32, 112, 112]   --          --
│    └─Sequential (1)                       [32, 32, 112, 112]  [32, 16, 112, 112]   --          Fal
se
│    │    └─MBConv (0)                      [32, 32, 112, 112]  [32, 16, 112, 112]   (1,448)     Fal
se
│    └─Sequential (2)                       [32, 16, 112, 112]  [32, 24, 56, 56]     --          Fal
se
│    │    └─MBConv (0)                      [32, 16, 112, 112]  [32, 24, 56, 56]     (6,004)     Fal
se
│    │    └─MBConv (1)                      [32, 24, 56, 56]    [32, 24, 56, 56]     (10,710)    Fal
se
│    └─Sequential (3)                       [32, 24, 56, 56]    [32, 40, 28, 28]     --          Fal
se
│    │    └─MBConv (0)                      [32, 24, 56, 56]    [32, 40, 28, 28]     (15,350)    Fal
se
│    │    └─MBConv (1)                      [32, 40, 28, 28]    [32, 40, 28, 28]     (31,290)    Fal
se
│    └─Sequential (4)                       [32, 40, 28, 28]    [32, 80, 14, 14]     --          Fal
se
│    │    └─MBConv (0)                      [32, 40, 28, 28]    [32, 80, 14, 14]     (37,130)    Fal
se
│    │    └─MBConv (1)                      [32, 80, 14, 14]    [32, 80, 14, 14]     (102,900)   Fal
se
│    │    └─MBConv (2)                      [32, 80, 14, 14]    [32, 80, 14, 14]     (102,900)   Fal
se
│    └─Sequential (5)                       [32, 80, 14, 14]    [32, 112, 14, 14]    --          Fal
se
│    │    └─MBConv (0)                      [32, 80, 14, 14]    [32, 112, 14, 14]    (126,004)   Fal
se
│    │    └─MBConv (1)                      [32, 112, 14, 14]   [32, 112, 14, 14]    (208,572)   Fal
se
│    │    └─MBConv (2)                      [32, 112, 14, 14]   [32, 112, 14, 14]    (208,572)   Fal
se
│    └─Sequential (6)                       [32, 112, 14, 14]   [32, 192, 7, 7]      --          Fal
se
│    │    └─MBConv (0)                      [32, 112, 14, 14]   [32, 192, 7, 7]      (262,492)   Fal
se
│    │    └─MBConv (1)                      [32, 192, 7, 7]     [32, 192, 7, 7]      (587,952)   Fal
se
│    │    └─MBConv (2)                      [32, 192, 7, 7]     [32, 192, 7, 7]      (587,952)   Fal
se
│    │    └─MBConv (3)                      [32, 192, 7, 7]     [32, 192, 7, 7]      (587,952)   Fal
se
│    └─Sequential (7)                       [32, 192, 7, 7]     [32, 320, 7, 7]      --          Fal
se
│    │    └─MBConv (0)                      [32, 192, 7, 7]     [32, 320, 7, 7]      (717,232)   Fal
se
│    └─Conv2dNormActivation (8)             [32, 320, 7, 7]     [32, 1280, 7, 7]     --          Fal
se
│    │    └─Conv2d (0)                      [32, 320, 7, 7]     [32, 1280, 7, 7]     (409,600)   Fal
se
│    │    └─BatchNorm2d (1)                 [32, 1280, 7, 7]    [32, 1280, 7, 7]     (2,560)     Fal
se
│    │    └─SiLU (2)                        [32, 1280, 7, 7]    [32, 1280, 7, 7]     --          --
├─AdaptiveAvgPool2d (avgpool)               [32, 1280, 7, 7]    [32, 1280, 1, 1]     --          --
├─Sequential (classifier)                   [32, 1280]          [32, 2]              --          Tru
e
│    └─Dropout (0)                          [32, 1280]          [32, 1280]           --          --
│    └─Linear (1)                           [32, 1280]          [32, 2]              2,562       Tru
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Fig. 3.2: Summary of EfficientNetB0

Table 3.1: Summary of Hyper_parameter

Hyper-parameter	**Value**
Batch_size	24
No of epochs	300
Learning rate	0.001
Optimizer	Adam
Dropout value	0.5

Table 4.1: Comparative Analysis

Study	**Model**	**Accuracy Score**
Jahanara et al. [12]	VGG19	0.84
Our	EfficientNetB0	0.85

4. Results and Discussion. We utilized the following evaluation metrics to assess the performance of the suggested classifiers.

1. **Accuracy:** The degree to which a classifier can correctly predict the class for a given input is known as classification accuracy. It is described as the proportion of accurate predictions out of all possible predictions that the classifier made.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

2. **Precision:** A classifier's precision, which is measured using a metric, is how well it predicts the positive class. Its definition is the proportion of the classifier's true positive predictions among all its positive predictions.

$$Precision = \frac{TP}{TP + FP} \tag{4.2}$$

3. **Recall:** The metric of recall assesses a classifier's ability to correctly identify each occurrence of the positive class. It is described as the number of true positive predictions made by the classifier out of all the positive cases in the dataset.

$$Recall = \frac{TP}{TP + FN} \tag{4.3}$$

4. **F1 Measure:** F1 measure is harmonic mean of recall and precision.

$$F1 - measure = 2\frac{Recall \times Precision}{Recall + Precision} \tag{4.4}$$

We demonstrate the effectiveness of the suggested technique in terms of accuracy, precision, memory, F1 measure, confusion matrix, and AUC score. The loss and accuracy curve from Fig. 4.1 indicates initially accuracy was high and gradually model shows smooth accuracy, and the maximum predicted value of accuracy is 0.85%. While in case of loss, training loss was initially significantly higher compared to test loss. Training loss gradually decreases, and the problem of overfitting is resolved. We also examine the batch accuracy and batch loss data. We identified the model's bias toward non-autistic class cases in terms of accuracy. We also evaluate the effectiveness of the suggested method in terms of recall and precision and F1-score. The bar graph of precision shows the proposed module is biased toward the non-autistic samples and shows more instances in predicting the non-autistic. While the recall is more biased toward the autistic samples and predicts more samples of autistic class. The F1 is average in both precision and recall. The overall description of classification report is shown in figure 4.2. We also display the confusion matrix on the test dataset, which displays instances that were properly and incorrectly predicted in figure 4.3. We also make comparison with one study to evaluate the effective of proposed technique

5. Conclusion. We can wrap up by mentioning this paper's three main contributions. (i) To address the issue of transfer learning, we presented an approach by using last three layers of EfficientNetB0 for detecting autism disorder as not having enough training data. The method is based on training the deep learning model with a balanced approach on a little amount of dataset (ii) Our designed approach is simple, efficient, and beats the baseline transfer learning techniques, (iii) we proposed techniques that showed outstanding results in terms of accuracy, with accuracy scores of 85% , precision , recall and F1-measure. This research shows

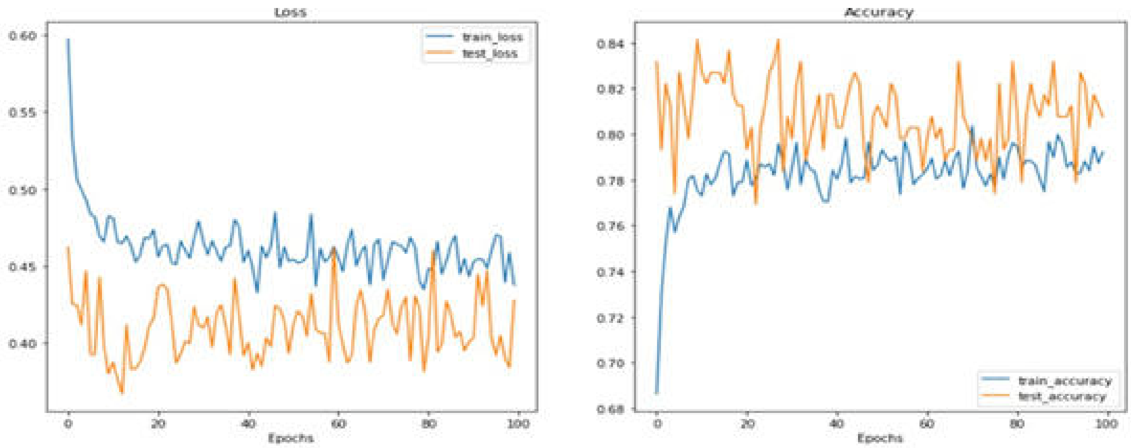

Fig. 4.1: Loss and Accuracy Curve

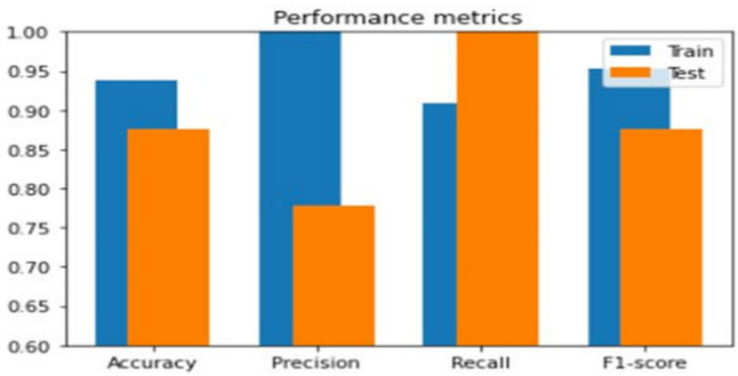

Fig. 4.2: Classification Report

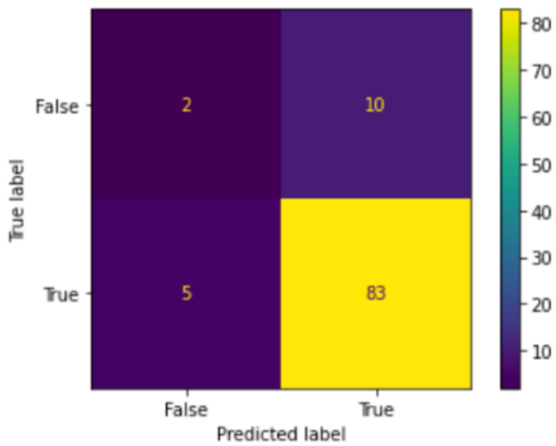

Fig. 4.3: Confusion matrix

that predictive analysis based on transfer learning using EfficientNetB0 from autism images is highly efficient and provides a simple path for automatic detection. In future, we are interested to explore the generative and transformer-based approaches for prediction of autism.

REFERENCES

[1] *https://drive.google.com/drive/folders/1xqu0plul0m3tilxqntano12d68pemb8a.*

[2] *https://www.kaggle.com/c/challenges-in-representation-learning-facial-expressionrecognition-challenge.*

[3] Z. A. Ahmed, T. H. Aldhyani, M. E. Jadhav, M. Y. Alzahrani, M. E. Alzahrani, M. M. Althobaiti, F. Alassery, A. Alshaflut, N. M. Alzahrani, and A. M. Al-Madani, *Facial features detection system to identify children with autism spectrum disorder: deep learning models*, Computational and Mathematical Methods in Medicine, 2022 (2022).

[4] F. W. Alsaade and M. S. Alzahrani, *Classification and detection of autism spectrum disorder based on deep learning algorithms*, Computational Intelligence and Neuroscience, 2022 (2022).

[5] S. Bebortta, S. S. Tripathy, S. Basheer, and C. L. Chowdhary, *Deepmist: Towards deep learning assisted mist computing framework for managing healthcare big data*, IEEE Access, (2023).

[6] M. Botha, B. Dibb, and D. M. Frost, *" autism is me": an investigation of how autistic individuals make sense of autism and stigma*, Disability & Society, 37 (2022), pp. 427–453.

[7] K. Campbell, K. L. Carpenter, S. Espinosa, J. Hashemi, Q. Qiu, M. Tepper, R. Calderbank, G. Sapiro, H. L. Egger, J. P. Baker, et al., *Use of a digital modified checklist for autism in toddlers–revised with follow-up to improve quality of screening for autism*, The Journal of Pediatrics, 183 (2017), pp. 133–139.

[8] F. Chiarotti and A. Venerosi, *Epidemiology of autism spectrum disorders: a review of worldwide prevalence estimates since 2014*, Brain sciences, 10 (2020), p. 274.

[9] T. Ghosh, M. H. Al Banna, M. S. Rahman, M. S. Kaiser, M. Mahmud, A. S. Hosen, and G. H. Cho, *Artificial intelligence and internet of things in screening and management of autism spectrum disorder*, Sustainable Cities and Society, 74 (2021), p. 103189.

[10] M. I. U. Haque and D. Valles, *A facial expression recognition approach using dcnn for autistic children to identify emotions*, in 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), IEEE, 2018, pp. 546–551.

[11] M.-P. Hosseini, M. Beary, A. Hadsell, R. Messersmith, and H. Soltanian-Zadeh, *Deep learning for autism diagnosis and facial analysis in children*, Frontiers in Computational Neuroscience, (2022), p. 119.

[12] S. Jahanara and S. Padmanabhan, *Detecting autism from facial image*, (2021).

[13] Y. Jin, C.-Y. Wee, F. Shi, K.-H. Thung, D. Ni, P.-T. Yap, and D. Shen, *Identification of infants at high-risk for autism spectrum disorder using multiparameter multiscale white matter connectivity networks*, Human brain mapping, 36 (2015), pp. 4880–4896.

[14] Y. F. Khan, B. Kaushik, C. L. Chowdhary, and G. Srivastava, *Ensemble model for diagnostic classification of alzheimer's disease based on brain anatomical magnetic resonance imaging*, Diagnostics, 12 (2022), p. 3193.

[15] M. Khodatars, A. Shoeibi, D. Sadeghi, N. Ghaasemi, M. Jafari, P. Moridian, A. Khadem, R. Alizadehsani, A. Zare, Y. Kong, et al., *Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: a review*, Computers in Biology and Medicine, 139 (2021), p. 104949.

[16] Y. Khosla, P. Ramachandra, and N. Chaitra, *Detection of autistic individuals using facial images and deep learning*, in 2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), IEEE, 2021, pp. 1–5.

[17] B. Li, S. Mehta, D. Aneja, C. Foster, P. Ventola, F. Shic, and L. Shapiro, *A facial affect analysis system for autism spectrum disorder*, in 2019 IEEE International Conference on Image Processing (ICIP), IEEE, 2019, pp. 4549–4553.

[18] R. Marotta, M. C. Risoleo, G. Messina, L. Parisi, M. Carotenuto, L. Vetri, and M. Roccella, *The neurochemistry of autism*, Brain sciences, 10 (2020), p. 163.

[19] P. McCarty and R. E. Frye, *Early detection and diagnosis of autism spectrum disorder: why is it so difficult?*, in Seminars in Pediatric Neurology, vol. 35, Elsevier, 2020, p. 100831.

[20] M. Mishra and U. C. Pati, *Autism spectrum disorder detection using surface morphometric feature of smri in machine learning*, in 2021 8th international conference on smart computing and communications (icscc), IEEE, 2021, pp. 17–20.

[21] L. Mottron and D. Bzdok, *Autism spectrum heterogeneity: fact or artifact?*, Molecular psychiatry, 25 (2020), pp. 3178–3185.

[22] K. Mujeeb Rahman and M. M. Subashini, *Identification of autism in children using static facial features and deep neural networks*, Brain Sciences, 12 (2022), p. 94.

[23] I. J. Oosterling, M. Wensing, S. H. Swinkels, R. J. Van Der Gaag, J. C. Visser, T. Woudenberg, R. Minderaa, M.-P. Steenhuis, and J. K. Buitelaar, *Advancing early detection of autism spectrum disorder by applying an integrated two-stage screening approach*, Journal of Child Psychology and Psychiatry, 51 (2010), pp. 250–258.

[24] S. Padinjappurathu Gopalan, C. L. Chowdhary, C. Iwendi, M. A. Farid, and L. K. Ramasamy, *An efficient and privacy-preserving scheme for disease prediction in modern healthcare systems*, Sensors, 22 (2022), p. 5574.

[25] S. Parisot, S. I. Ktena, E. Ferrante, M. Lee, R. Guerrero, B. Glocker, and D. Rueckert, *Disease prediction using graph convolutional networks: application to autism spectrum disorder and alzheimer's disease*, Medical image analysis, 48 (2018), pp. 117–130.

[26] P. K. C. Prasad, Y. Khare, K. Dadi, P. Vinod, and B. R. Surampudi, *Deep learning approach for classification and*

interpretation of autism spectrum disorder, in 2022 International Joint Conference on Neural Networks (IJCNN), IEEE, 2022, pp. 1–8.

[27] D. A. Rossignol and R. E. Frye, *Melatonin in autism spectrum disorders: a systematic review and meta-analysis*, Developmental Medicine & Child Neurology, 53 (2011), pp. 783–792.

[28] S. R. Shahamiri and F. Thabtah, *Autism ai: a new autism screening system based on artificial intelligence*, Cognitive Computation, 12 (2020), pp. 766–777.

[29] B. K. Swain, M. Z. Khan, C. L. Chowdhary, and A. Alsaeedi, *Src: Superior robustness of covid-19 detection from noisy cough data using gfcc*.

[30] K. Tait, F. Fung, A. Hu, N. Sweller, and W. Wang, *Understanding hong kong chinese families' experiences of an autism/asd diagnosis*, Journal of Autism and Developmental Disorders, 46 (2016), pp. 1164–1183.

[31] M. Tan and Q. Le, *Efficientnet: Rethinking model scaling for convolutional neural networks*, in International conference on machine learning, PMLR, 2019, pp. 6105–6114.

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