Identification of Autism Spectrum Disordered kids from Normal Crowd using Attention based Deep Learning Technique

Abstract

Autism Spectrum Disorder (ASD) is a developmental disorder found in early childhood. This neurological disorder affects the way children act in society and interact with others. Usually, ASD kids are associated with excess emotional facial-expressions or poor emotional facial-expressions. The primary objective of this paper is to use deep learning techniques to identify ASD kids from the normal crowd by analysing their facial expressions. Several videos of ASD kids and normal kids were collected. These videos were then parsed into images to train an Attention based Residual Neural Network. This proposed model brings a novel method of embedding Attention on Residual Convolution Neural Networks, which results in carrying the most significant dominating features from the initial layers to the very end with very little distortion. This is done by the attention block, which weighs every parameter according to its significance. This way, the features with higher weighs are passed till the deep layers of the network without any loss of information. Thus, the proposed work is able to classify effectively the ASD kids from the normal ones based on the videos collected successfully yielding results with a state-of-the-art accuracy of around 93%.

1. Introduction:

There has been a significant increase in data acquisition, storage, and production over the last twenty years. The variety of data generated in the big data is marked by a significant increase in the data rate produced. Data diversity, size increase, and speed are attributed to the affordability and availability of various resources and infrastructure. It is wide range used to collect and analyse a variety of information.

For more information, numerous machine learning tools available, such as Hadoop, has given researchers unique opportunities to develop machine learning algorithms with advanced hardware TensorFlow, Spark and R. Across various studies, the rise across computing power and processing technologies has opened the door to apply the machine learning theories.

Another such field is research into the Autism Spectrum Disorder. Autism spectrum disorder is a disorder which affects neurodevelopment. It is defined by the social interaction and social interaction impairments. However, patterns of restrained, repeated behaviour (Vahia, 2013). The Centres for Disease Control and Prevention (CDC) currently has one of 59 children in the United States who are diagnosed with ASD (Christensen et al., 2018). That can be undervalued based on recent results in a Parent Survey finding a prevalence rate of 45 (Zablotsky et al., 2015).

Autism spectrum disorder is a multi-factorial Characterized by illness by presence and severity of symptoms, risk factors and diagnosis, and reaction to treatment Lord(Lord et al., 2000). Autism spectrum disorder is the high prevalence rate and complexity has prompted some researchers to move to machine learning over conventional methods of statistical data analysis.

Training machines can be narrowly divided in to two groups, such as unmonitored and unmonitored learning. Supervised machine learning involves the use of input variables to predict categorical or continuous target classification. Like Unattended learning, supervised learning involves data sets where the data used to learn the model is predicted is established during preparation.

The supervised learning model is considered successful when, outside model testing, the target decision for a training data set can be predicted correctly with a certain degree of accuracy and extended into new data sets. A process called cross-validation is also used to improve the ability of a model to make predictions on future data.

This paper is mainly focuses on human computer communication via facial expressions. Social communication is the use of verbal or verbal communication to communicate with people. This includes speech, body postures, gestures, visual acuity, and facial expressions used to communicate and respond to others. Autistic children face major difficulties

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in understanding social references and conventions. They are unable to articulate non-verbal communication and body language.

These impairments prevent them from understanding verbal and non-verbal communication and effectively reading human facial expressions. The ability to detect and determine one's emotions can be an empowerment for the field of artificial intelligence and lead to intelligent, powerful machines that understand the intent of users. An intelligent machine with emotional awareness can achieve the disabilities of children with autism. With that emotional awareness, the autistic child has the power to teach and guide the person who he or she is interacting with and how to respond appropriately when they express various emotions (Mower et al., 2010). Such a machine has the potential to reduce the communication gap between society and people with depression.

2. Related works:

Automated ASD Screenings are several facial expressions computational models that automatically identify people with ASD. Anzulevich et al.(Anzulewicz et al., 2016) use smart tablet devices to record children's facial expression patterns, and propose three results - face use models for identifying ASD based on these patterns.

ASD inspired by the findings that individuals with difficulties recognize faces and interpret facial emotions Liu et al. (Liu et al., 2016),(Sasson et al., 2011) evaluated the scanning methods of children's facial expressions and assessed ASD. In order to detect differences in facial appearance patterns between the ASD and the control group when viewing the image, Wang et al.(Wang et al., 2015) proposes to provide a training model with a predefined features support vector machine (SVM) model to classify persons with ASD according to their perspective. Jiang and Zhao (Jiang & Zhao, 2017) then extend the idea (Wang et al., 2015) by introducing a new deep neural network approach, which highlights the differences in visual patterns, resulting in more discriminatory features for accurate ASD screening. People have also explored a variety of neuroimaging techniques for classifying ASD. These observations are tabulated in Table (1).

From Table (1). represents the existing techniques to identify ASD kids from the normal crowd. It can be noticed from the table that different feature extraction techniques has been used by them. All of the used techniques weighs all the features of the input equally thus leading to some information obtained in the initial layers being lost as the network goes deeper. Hence, the proposed system is architected in such a way that it weighs the significant parameters more than the rest and thereby making the model more efficient in terms of feature extraction.

Table 1. Related Works

Reference	Feature Extraction	Database	Sample size	Performance
Daniel Bone (Bone et al., 2015)	Computational and behavioural sciences converge	ADOS	984 subjects 942 Autism and 30 TD	Don't generalize the code collection or classification across datasets
Omar RIHAWI (Rihawi et al., 2017)	Behaviours and provides researchers with a benchmark data set	3D autism dataset	-	Dynamic time warping demonstrate good understanding of static and dynamic behaviours
Mahsa Naeeni Davarani (Davarani et al., 2017)	Identify and Categorize children with faces emotions	DSM-5	80 children with autism disorder	An automatic system for identifying the range of autistic children
Marguerite Marlow (Marlow et al., 2019)	Improving the scientific rigor of early detection approach	Psychometric Data	300 sample with 70% of ASD	Small numbers of qualified and educated health workers in ASD and DD.
Kayleigh K. Hyde (Hyde et al., 2019)	Face classification	ADI-R and SRS	29 ASD children with ages 4 to 11years.	Classification and supervised learning is not useful up to level.
Amy Stedman (Stedman et al., 2019)	Wide variability in measurement and reporting	PsychInfo CINAHL (EBSCO) Cochrane PubMed	367 sampled males, 335 sampled females.	Increase the interpretability of observations by using a simpler and more coherent explanation of samples
Arnaud Dapogny (Dapogny et al., 2018)	children how to produce Facial expressions	JEMImE	157 children with Age (6 to 11 years)	In JEMImE-All database, FE classification average scores
Shashank Jaiswal (Jaiswal et al., 2017)	3D analysis of behaviour with Dynamic Deep Learning	KOMAA	55 subjects with 18years	Accuracy of 93.9%.
Shi Chen (Chen & Zhao, 2019)	first computational model to classify people with ASD	Saliency4ASD	45 samples	achieve the distilling knowledge across the two modalities
Jing Li (Li et al., 2019)	Gaze patterns between ASD	272 videos - 136 ASD childrens	136 Negative classes, 53 Positive classes	Sensitivity - 91.9% Specificity - 93.4%.
Ming Jiang (Jiang & Zhao, 2017)	Dynamic Affect Recognition Evaluation (DARE)	696 subjects	23 subjects with ASD and 35 controls	86% - Classification accuracy
Eunji Chong (Chong et al., 2017)	Pose-Implicit CNN	Georgia Tech Child Study Lab dataset	22 hours of 156 recordings from 100 ASD Children's play session	Precision - 0.76 Recall - 0.80.
Md Inzamam Ul Haque (Haque & Valles, 2018)	DCNN ASD images from different angles.	Karolinska Directed Emotional Faces KDEF	500 Training images - Validation 100 - Testing.	training - 89.76% validation - 80.82%. test accuracy - 78.32%.
S.P. Abirami (Abirami et al., 2019a)	Identify children who may soon fall under autistic traits.	193 -ASD POSITIVE 359 - ASD NEGATIVE	304 and 390 images	Linear SVM classifier - 0.811594202899 .
Jing Li (Li et al., 2018)	Automatic identification of children with ASD in raw video	189 videos 53 - ASD 136 TD	DSM-IV	Classification Accuracy - 93.7%.
Wenbo Liu (Liu et al., 2016)	to classify children with and without ASD.	29 - 4 to 11year ASD	18 Novel faces	Classification accuracy - 88.51%.
Alanoud Bin Dris (Dris et al., 2019)	The gaze-based screening with the identifying ASD	29 participants	29 ASD children	Accuracy is 88.6% Specificity is 92.31% Sensitivity is 86.63% AUC score is 0.96.
Qandeel Tariq (Tariq et al., 2018)	MLA for Identify ASD	116 short home videos	Mean age - 4 years 10 mon SD - 2 years 3 months	sparse 5-feature LR classifier - 92%
Alexis Nebout (Nebout et al., 2019)	Saliency prediction model for children with ASD.	MIT1003 dataset	300 images	CC score of 0.8992 and 0.8653
Suzan Anwar (Anwar & Milanova, 2016)	Active shape Model (ASM) tracker	CAFE set	1192 images	93% classification accuracy.
Marco Leo (Leo et al., 2018)	facial expressions produced by ASD children	Extended CohnKanade Dataset (CK+)	327 images 17 children with ASD	Average score among children - 89.1341
Yudong Tao (Tao & Shyu, 2019)	SP-ASDNet, using both CNNs and LSTM	Saliency4ASD	300 images	74.22% accuracy for validation.
S.P. ABIRAMI (Abirami et al., 2019b)	Using facial landmark vectorization, the facial features are marked, and expressions are categorized using a linear classifier of SVM.	193 -ASD POSITIVE 359 - ASD NEGATIVE	304 and 390 images	CNN - 0.89754.
Huiyu Duan (Duan et al., 2019)	Design of specialized educational content for children with ASD that contains human face	ASD (SPCA) Dataset Saliency Analysis for children	481- source images	In children with ASD, expect visual attention on the human face.
Uzma Haque Syeda (Syeda et al., 2017)	The patterns of visual facial scanning and emotion recognition between	42 - 21ASD & 21TD	14 Male & 7 Female Age - 5 to 17years	Male Accuracy - 68.29%
Vikas Khullar (Khullar et al., 2017)	Autistic facial expressions during the execution of their motor movements using a computerized approach	NIMH-ChEFS	10 ASD 10 TD (16 male and 4 female) (4 12 years)	emotions with 53 as maxi &27 as min for ASD 68 as maxi and 49 as mini for TD
Wataru Sato (Sato et al., 2017)	comparing TD and ASD individuals	51(26 females & 25 males) age 22.5 4.5 years	Total - 34 17 ASD (12 Males & 5 females) 17 TD (12 males and 5 females)	Normal - 96.4 4.0, Anger - 94.1 5.9 Happiness - 97.1 2.4

3. Proposed work:

This work proposes a novel deep learning technique for micro-expression analysis to classify ASD kids from normal ones. The proposed model is Attention based Residual network. This model carries the dominating features obtained in the early layers till the very end of the neural network without distortion. Thus resulting in very less valuable information loss. The primary focus of this paper is to construct a less computationally expensive yet an accurate model to identify and classify ASD kids from the rest. Not like conventional Convolution Neural Network (CNN) model which gives equal weights to all features (Karthik et al., 2020), the proposed model weighs every parameter based on its significance. This way, high significant parameters are given higher weights with the use of Attention blocks. The parameters with higher weights are carried on till the last layer, thus making the model more precise and accurate in classification.

3.1. Attention embedded Residual Network:

Conventional CNN model equally weighs all the parameters as the learning happens from the aggregated feature map from different layers. The disadvantage of this pattern of learning is that it losses some critical and significant information learned in the primary layers as it treats all the features the same. Hence in the proposed model the significant information learned in the early layers are passed to the deeper layers. This architecture is achieved by embedding attention mechanism to the residual network. The Attention block weighs the significant parameters higher than the rest. This way, the model will be able to achieve precise classification of micro-expressions.

Fig (1). represents architecture of the model. The proposed model consists of three Residual blocks connected in sequence. At the end, average pooling to avoid over-fitting.

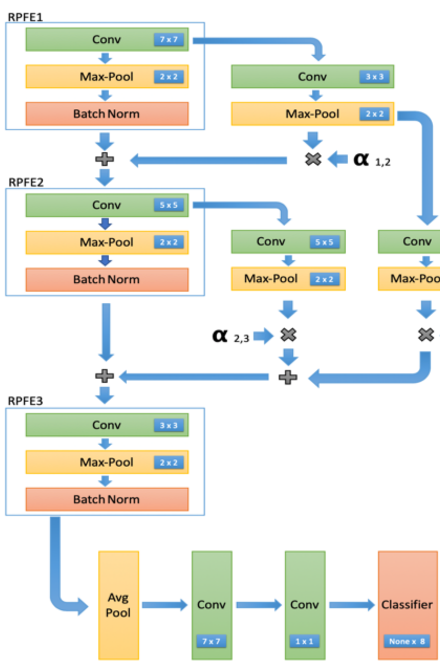

Figure 1. Architecture of the proposed model

3.2. Residual blocks and attention mechanism:

The proposed model consists of three Residual blocks connected in sequence. A convolution layer, Max-Pooling layer, and a Batch Normalization layer builds a residual block. Zero padded input feature map is convoluted with distinct kernels in the convolution layer. This is then followed by an activation function, Rectified Linear Unit (ReLU). ReLU function removes all the negative values from the feature map and replaces them with zeros, thus remaining the shape unchanged and adding stability to it.

The feature map obtained after ReLU function is passed to two branches: A(x) containing a Conv layer, Max-Pool and Batch Norm layer, and B(X) containing a Convolution and Max-Pool layer with attention embedding. This attention embedding block in B(x) learns and weighs the parameters according to their significance. The input to the next block Y(x) is obtained by adding the output of A(x) and B(x) and this equation is presented in Eq (1).

The Architecture of the proposed model are shown in Figure (1).

$$Y(x) = A(x) + B(x) * \alpha \tag{1}$$

Where, α is the Attention weight matrix.

The α and the resultant of operation of B(x) have the same dimension. Point wise multiplication is done between α and B(x). The α is learned by passing the B(x) through the dense block, which learns α i,j depending on cross-section of each pixel of B(x)i,j. This learning process is shown in Fig (2) (Karthik et al., 2020). Where (i) represents the Feature map of B(x), (ii) represents the A ReLU activated dense layer matrix, (iii) Softmax activation layer and (iv) Computed B(x)* α as in Eq (1).

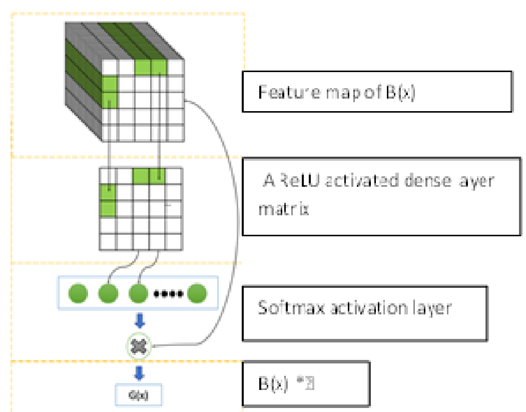

Figure 2. Learning process of α, activation matrix (Karthik et al., 2020)

Fig(3) shows the flow process of the Residual blocks with A(x) and B(x).

4. Results and Discussions:

Videos collected manually from ASD kids and normal kids were used to train the proposed deep learning model. The videos captured the childrens reaction and micro-expression in response to the same set of videos. We then generated a CSV file which maps the videos with their labels. The videos were then parsed and each frame was considered as

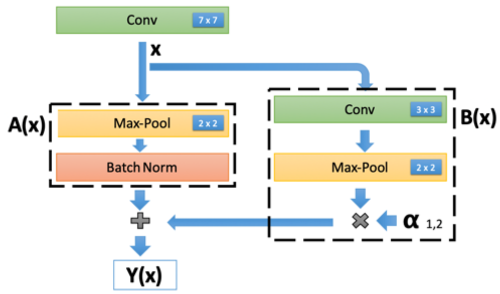

Figure 3. Flow of A(x) and B(x) functions and their summation to generate Y(x)

Table 2. Train Test split-up of data

Split-up	Number of images
Training	1,02,032
Testing	25,012
Total	1,27,044

an image in the training and testing process. The proposed model was built using TensorFlow framework. To minimize the loss function gradually as the learning happens, Adaptive Moment Estimation (Adam) optimizer was used. The Adam optimizer is an adaptive function which minimizes the loss function gradually as the learning happens.

The split-up of train and test data is presented in Table (2). The results of training and testing are tabulated in Table (3).

5. Dataset:

Dataset generation included collecting videos of 5 ASD kids and 8 normal kids. Videos collected manually from different normal and ASD kids were used for training and testing of the proposed model. These videos were then split frame wise into 1,27,044 images. The obtained images were then resized to 256x256 dimension to standardise them. The sample of the images created are tabulated in Table IV. The manually created CSV file is then used to map these images with their label and to convert the results in the form of an NPZ file. The model training, validation and testing was done using this NPZ file. 70 to 30 split ratio was used between training and testing data. The obtained training accuracy graph and training loss function graph are presented in Fig (4).

Table 3. Results of training and training

Metrics	CASME I
Number of Epochs	20
Training Accuracy	98.54%
Testing Accuracy	92.71%

Figure 4. Sample Dataset images

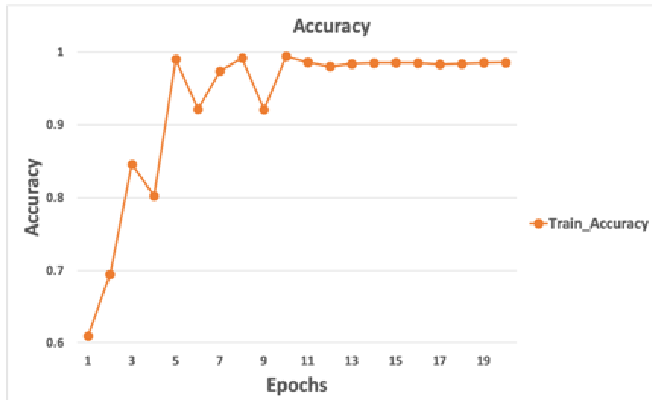

Figure 5. Accuracy Graph

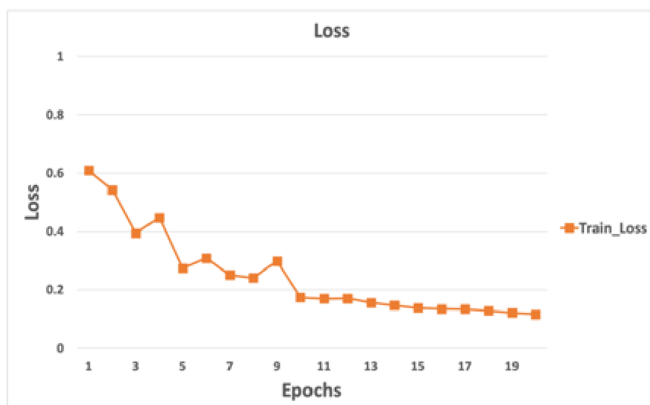

Figure 6. Loss Graph

6. Performance Analysis:

The metrices and the feature extraction techniques of the already existing and proposed models are tabulated in Table I under the literature survey section. Instead of weighing all the parameters equally, the proposed system weighs them according to their significance. The proposed model achieves an accuracy of 92.71%. Hence, the proposed deep learning architecture stands as one of the significant improvement in terms of precision and accuracy in identification of ASD kids from the crowd.

7. Conclusion

The proposed Attention based Residual CNN deep learning architecture is able to classify the ASD kids from the normal ones with high efficiency. The primary focus of this work was to apply attention mechanism to infer vital information from facial expressions. The proposed model learns and weighs each and every feature according to its significance so that the important parameters obtained in the earliest layers are passed to the deeper layers of the network and hence providing high accuracy and stability. The uniqueness about the proposed model is that it can classify the ASD kids from the normal ones just from the videos collected at random time stamps and environments. So any instance of the kids captured as an image or video can be used to get the classification results. There is no specific scenario or situation where the kid has to be fit in order to achieve accurate classification. Experimental results obtained in manual videos collected from ASD and normal kids gave an testing accuracy of around 93%. The future extension for this proposed model is to generalise this identification process over all age categories including adults and elderly people.

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