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Autism Spectrum Disorder Classification And Prediction

DARSHIKA KELIN A.R
ASSISTANT PROFESSOR
CSE ST.JOSEPH'S
INSTITUTE OF
TECHNOLOGY
CHENNAI, INDIA
darshikakelin5@gmail.com

SURENDAR S
STUDENT CSE
ST.JOSEPH'S
INSTITUTE OF
TECHNOLOGY
CHENNAI, INDIA
surendarsenthilvelan@gmail.com

SAKTHIVEL
SIVANANTHAM
STUDENT CSE
ST. JOSEPH'S
INSTITUTE OF
TECHNOLOGY
CHENNAI, INDIA
sivasakthi992002@gmail.com

Abstarct

Autism Spectrum Disorder (ASD) which is a neuro development disorder , is often accompanied by sensory issues such an over sensitivity or under sensitivity to sounds and smells or touch. Although its main cause is genetic in nature, early detection and treatment can help to improve the conditions .In recent years, machine learning based intelligent diagnosis has been evolved to complement the traditional clinical methods which can be time consuming and expensive. The focus of this paper is to classify the ASD and NON ASD and improve the accuracy using Tensor Flow 2(Keras) and Support Vector Machine (SVM) to obtain an accuracy of 99% from the our ASD and NON ASD datasets. The existing accuracy was 98.35 which we improved to 99% that gives better output.

I. Introduction

Autism spectrum disorder (ASD), is a neurological developmental disorder. It affects how people communicate and interact with others, as well as how they behave and learn . The symptoms and signs appear when a child is very young. It is a lifelong condition and cannot be completely cured. A study found that 33% of children with difficulties other than ASD have some ASD symptoms while not meeting the full classification criteria

A diversity of computer-aided technologies has been embraced to help with the detection of autism. Examples include Magnetic Resonance Imaging, Electroencephalography, and eye-tracking that is the focus of this study. The eye-tracking technology received quite particular attention in the ASD context whereas abnormalities of eye gaze have been consistently recognized as the hallmark of autism in general.

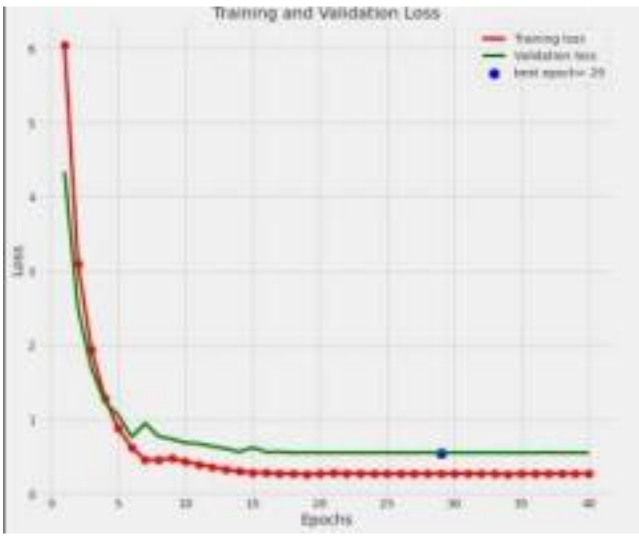
In addition, the adoption of AI-enabled applications is increasing in a rapid pace, which brings up further capabilities to support the diagnosis process. As part of that effort, this study provides a meeting point for eye-tracking and Machine Learning (ML) in the ASD context. The core idea is based on compactly rendering eye-tracking recordings into a visual representation that can illustrate the scan path of gaze movement. Using unsupervised ML, it was attempted to discover data-driven insights underlying such visual representations. The study is part of interdisciplinary collaboration between research units of Psychology and AI.

Ii. Description

The study comprised of 2000+ images of autistic and non autistic children to detect autism. These images are organized into two groups: ASD, non-ASD. We classified the test images with the help of Tensor Flow Library – Kerasusing Python. These datasets are then split into 2 classes: autistic and non-austic with average image height and average image width ratio. The model is trained in such a way that it can able to differentiate the people with autism and non-autism using Efficient Net – Image Classification

fine-tuning. It requires a initial model learning rate. Thereby, create a custom Keras callback to continue training the model with a maximum rate of 40 approaches. End of the results, It is found that the loss initially was at 6.0513 was dropped to 0.2685 and accuracy of the model was about 0.7102 at the start and after completion of the model training it has achieved 0.9956 which was about 99.5% accuracy score.

A graph is plotted against Training and Validation Loss:



Parallelly, we plotted another graph which contains the Training and Validation Accuracy Model graph as mentioned below :

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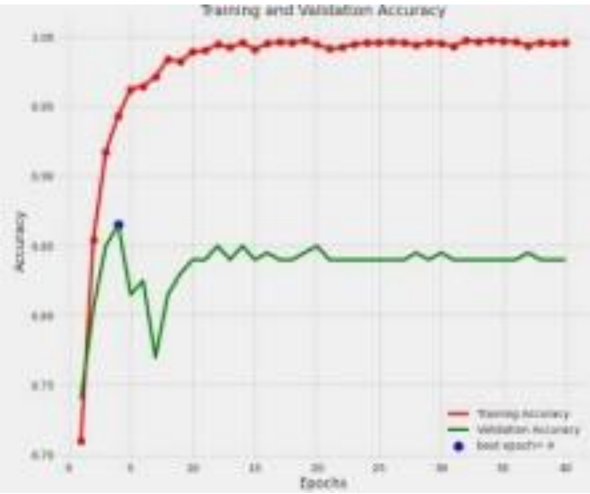
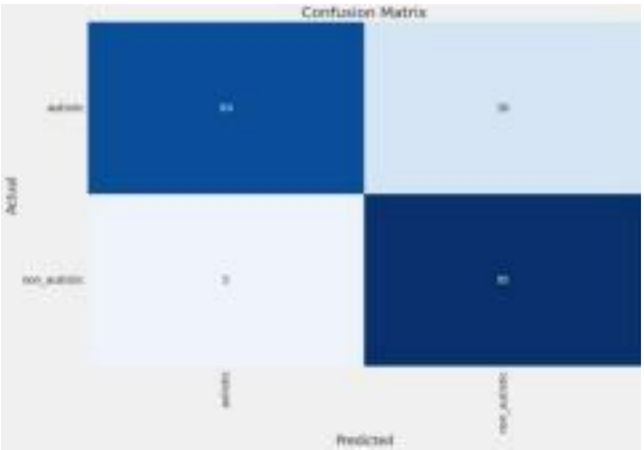


The graph shows that at epoch = 4, the validation accuracy of the model reached its peak and thereby has some variations along the epochs which take place further. Further, the accuracy of the model increases gradually and ends at 0.99. A test generator is created which generates predictions on the test set including a confusion matrix and a classification report is generated at the end. The results found there were 21 errors in 200 tests for an accuracy rate of 89.50.
282. This was done to reduce training time at the expense of the F1 score.

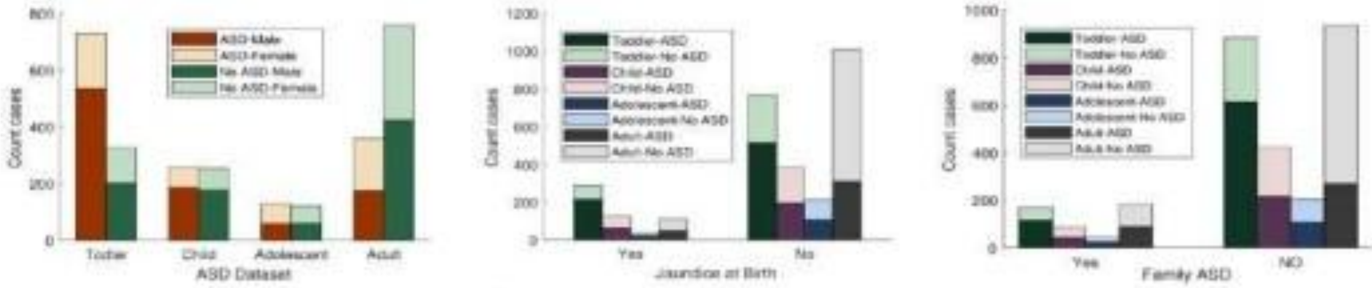
Iii Asd And Non-Asd



[redacted]

Weighted avg	0.8998	0.8950	0.8947

We achieved an F1 score of 83.6% which is not to be bad considering we limited the number of images in train_df to 150. Images per class and reduced the image size to 200 x

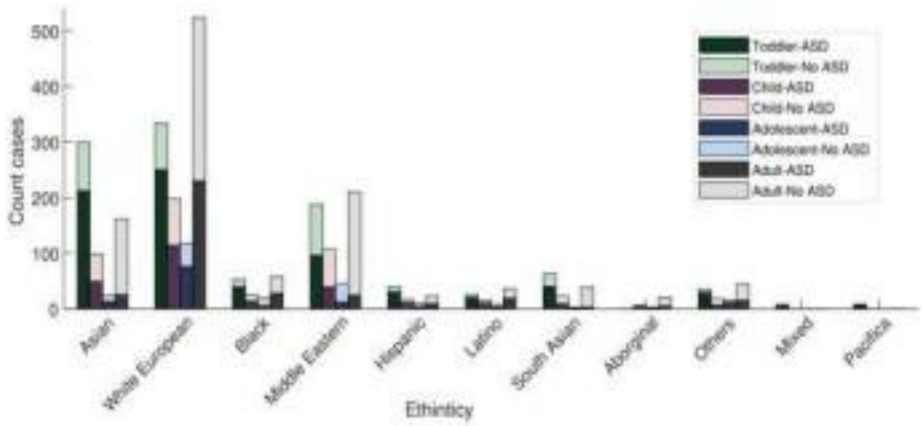


a Gender-wise distribution of ASD cases

b Impact of 'jaundice at birth' on ASD

c Impact of 'family ASD' on their off-spring ASD

IV SURVEY



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V Evaluation Matrix

For a given dataset and a predictive model, every datapoint will lie on one of the below four categories.

– True Positive (TP): The individual having ASD and iscorrectly predicted as having ASD.
– True Negative (TN): The individual not having ASD and was correctly predicted as not having ASD. – False Positive (FP): The individual not having ASD, is incorrectly predicted as having ASD.
– False Negative (FN): The individual having ASD, isincorrectly predicted as not having ASD.

Those categories are used to compute the following evaluationmatrix:
Accuracy: it is the measure of correct predictions madeby the classifier. Accuracy is the number of correctly identified predictions by total number of predictions:

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

Precision: it measures the accuracy of positive predictions. It is the ratio of true positive out of the total observed positive

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

Recall/Sensitivity: this is also called true positive rate. It is the proportion of samples that are genuinely positive by all positive results obtained during the test.

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

F-Measure: The F-score (or F-measure) considers boththe precision and the recall of the test to compute the score.

F-Measure(F1) = 2 x PrecisionPrecision + R

Vii Conclusion

In this study, we have analyzed the ASD datasets of toddler, child and adolescent .We apply the high level API of TensorFlow 2(Kera's) for image processing to train the model and achieved a accuracy of about 98.3% in Epoch10 and on further processing of the image datasets till Epoch40, the accuracy of the model was about 99.56% and the training elapsed time was about 1 hour.

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