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Original Paper

MEDICAL DATA PREPARATION WITH AUGMENTATION TECHNIQUES FOR DETECTION OF ASPERGER SYNDROME

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ABSTRACT

Asperger syndrome starts to appear in childhood and continues to keep going on into adolescence and adulthood. Propelled by the rise in the use of machine learning techniques in the research dimensions of medical diagnosis, this paper there is an attempt to explore the possibility to use VGG16, Mobilenet v2, Densenet-121, Resnet-51, Inceptionv3, and Convolution Neural Network for predicting A novel data-set is created with ASPERGER SYNDROME individuals of a toddler, adolescent, and adult age groups to evaluate the model. The first data set related to ASPERGER SYNDROME screening in children has 292 instances and 21 attributes. Second data-set related to ASPERGER SYNDROME screening. Adult subjects contain a total of 704 instances and 21 attributes. The third data-set related to ASPERGER SYNDROME screening in Adolescent subjects comprises 104 instances and 21 attributes. ACGAN is applied to increase the data set as there is an imbalance of data between healthy individuals and healthy individuals. After applying various deep learning architectures results strongly suggest that CNN-based prediction models work better on increased data sets with higher accuracy of 99.53, 98.30, and 96.88 % ASPERGER SYNDROME Screening in Data for Adults, Children, and Adolescents respectively.

KEYWORDS

ASPERGER SYNDROME Spectrum Disorder, ACGAN, Machine Learning, Densenet-121

1. Introduction

Asperger syndrome also referred to as ASPERGER SYNDROME is mainly detected by visual observation and analysis of children’s natural behaviours. There are certain limitations in the gold standard observational tool available that hinder the early screening of ASPERGER SYNDROME in children. So the most important things to be included in diagnosis include screening processes of child observations, parent interviews, and manual testing1 are costly and time-consuming2. While, the validity of the results obtained from a clinician’s observations can be subjective3, furthermore, behavioural rating capture data from the children's clinics not in their natural environments; these limitations are the motivation for the development of new methods of ASPERGER SYNDROME diagnosis without compromising accuracy, to reduce waiting periods for access to care. Accurate diagnosis is critical as an early intervention within the first few years of life can provide long-term improvements for the child and prove to be very effective4.

Retrospective analysis of home videos has helped to discover early behavioural risk markers of ASPERGER SYNDROME 5, 6, 7. Some of the documented ASPERGER SYNDROME-related behavioural markers documented by researchers that emerge within the first months of life are:

a. Diminished social engagement and joint attention8,9,

b. Atypical visual attention such as difficulty during response-to-name protocol10,

c. Longer latencies to disengage from a stimulus if multiple ones are presented11,

d. Non-smooth visual tracking12.

e. Decreased attention to social scenes,

f. Decreased frequency of gaze to faces13

g. Decreased expression of emotion.

h. Differences in motor control are an early feature of ASPERGER SYNDROME14, 15, 16, 17.

Computer vision has been used over the past decade, in the field of automated medical diagnosis as it can provide unobtrusive objective information on a patient's condition. Utilizing computer vision methods to automatically detect symptoms can pre-diagnose over 30 conditions as suggested by recent studies18. For example,

a) computer vision-based facial analysis can be used to monitor vascular pulse,
b) assess pain,
c) detect facial paralysis,
d) diagnose psychiatric disorders

The main reasons for using computer vision for a clinical purpose are
Ø to remove any potential bias,
Ø develop a more objective approach to analysis,
Ø increase trust towards diagnosis,
Ø decrease errors related to human factors in the decision-making process,
Ø Computer vision-based systems provide a low-cost and non-invasive approach, potentially reducing healthcare expenditures when compared to medical examinations.

2. Literature Survey

The commonly implemented ML algorithms are Random Forest (RF), Support Vector Machines (SVM), Alternative Decision Tree (AD Tree), and Logistic Regression (LR), Naïve Bayes, and K-Nearest Neighbour (KNN). The Table1 shows the details of work till now done on MRI imaging using machine learning for detection of ASPERGER SYNDROME. Computer vision has been used to capture and quantify different information, to study ASPERGER SYNDROME Spectrum Disorder:

Table1: Magnetic resonance imaging (MRI)/functional MRI (fMRI).

Reference	Focus	Participants	Age	Input data	Method used	Dataset
Samson et al.22	fMRI to study the neural bases of complex non-social sound processing	15 ASPERGER SYNDROME, 13 TD	ASPERGER SYNDROME: 24.3 ± 6.25 TD: 23.5 ± 7.42	fMRI scans/3 T TRIO MRI system	Image processing/ICBM152 (MNI) space and 3D Gaussian Filtering	Own dataset
Ahmadi et al.25	fMRI for biomarker detection	24 ASPERGER SYNDROME,		MRI scans/3T MRI	Machine learning, independent component analysis	Own dataset

		27 TD		scanner		
Eslami and Saeed28	fMRI for diagnosis	187 ASPERGER SYNDROME, 183 TD		fMRI scans	Deep learning, MLP with 2 hidden layers + SVM	Four datasets (NYU, OHSU, USM, UCLA) from ABIDE-I fMRI dataset
Crimi et al.30	fMRI for diagnosis	31 ASPERGER SYNDROME, 23 TD		Imaging data, GE 3T MR750 scanner	Machine Learning/Constrained Autoregressive Model	San Diego State University cohort of ABIDE II dataset
Chanel et al.32	fMRI for diagnosis	15 ASPERGER SYNDROME, 14 TD	ASPERGER SYNDROME: 28.6 ± 1.87 TD: 31.6 ± 2.61	fMRI/3T MRI scanner	Machine learning/SVM	Own dataset
Zheng et al.34	MRI for biomarker detection	66 ASPERGER SYNDROME, 66 TD		MRI scans	multi-feature-based networks (MFN) and SVM	4 datasets (NYU, SBL, KUL, ISMMS) from ABIDE database

2.1. Motivation

Researchers have proved that using conventional machine learning approaches and deep learning based models have proved effective for the detection of ASPERGER SYNDROME Spectrum Disorder. Here, several machine learning models performances have been compared for early detection purpose. Different models have been used on different dataset and then performances are compared individually. We have seen promising results given my machine learning algorithms for the assessment of ASPERGER SYNDROME. Mostly used tools for screening of ASPERGER SYNDROME are ADI-R and ADOS-G. Most common machine learning algorithms used are SVM, decision tree, random forest. But still there are many challenges with these algorithms for the implementation of computer aided assessment of ASPERGER SYNDROME. There is still some more research required for presenting a cost-effective novel computer-aided approach to prove the reliability of assessment results predicted by a deep learning or machine learning based algorithm.

2.2. Aim

1. The main aim of this study is to develop a model facilities imaging technology through screening of MRI of ASPERGER SYNDROME individuals. They lack in need of expert intervention for inference. A machine learning algorithm is trained with ASPERGER SYNDROME patient data such that it can classify between healthy and diseased individuals.

2. Here different deep learning algorithms have been used and performances have been compared for this purpose. A novel dataset has been created for this purpose with ASPERGER SYNDROME individuals of toddler group, children group and adult group.

3. In this work we focus on face dataset generation of ASPERGER SYNDROME toddler, child, adolescent. We present a novel and effective pipeline for generating face dataset from unlabelled and raw data images. There has been more than 70 individuals both girls and boys of different age group.

4. To bridge the data imbalance of ASPERGER SYNDROME kids' vs healthy individuals ACGAN has also been used here. These shows the performances of all algorithms have improved with increased datasets.

To fulfil this aim the following goals are set in a step-by-step manner.

• Fast and accurate result.
• Reduce human errors and bias.
•Low-cost approach.

3. METHODOLOGY

Current data augmentation techniques use simple techniques like image transformations and colour adjustments, such as scaling, converting, improving contrast, etc. that is fast, reliable, and easy. However, here we have a slightly altered sample, the changes are limited because it is structured to turn an existing sample whereas, classical data augmentation produces partially seen data.

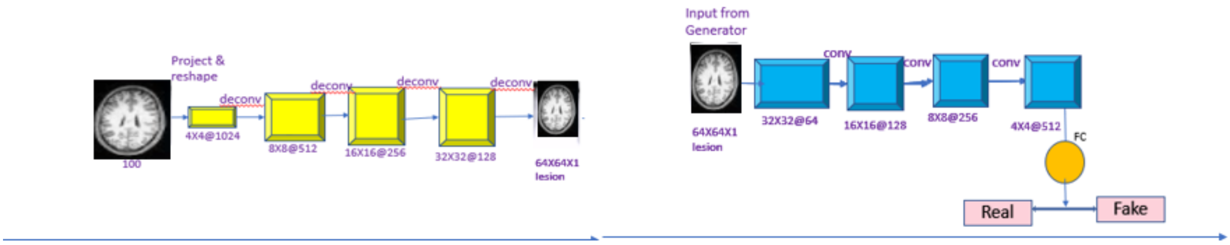

Figure 1 ACGAN architecture explained.

To overcome the limitations of classical data augmentation a modern, innovative, and advanced form of augmentation is Generative Adversarial Network (GAN) which helps to make synthetic images. There are two networks used in GAN:

G (z) (G(z) generator) and

D (z) (D(z) discriminator),

where the generator aims to produce a realistic image to trick the discriminator that is well trained to better differentiate between the real and fake images. The purpose of the generator is to minimize the cost value function. To reduce human interpretation computer image classification is used which helps to analyse and classify images into certain categories. Because researchers mostly focus on image classification and image feature extraction and classification algorithms. SIFT and HOG are traditional images features that involve manually designed. So, it triggered automatically features extraction methods by using the prior knowledge of the known categories and helped to avoid the traditional image classification methods which were a complicated process of feature extraction.

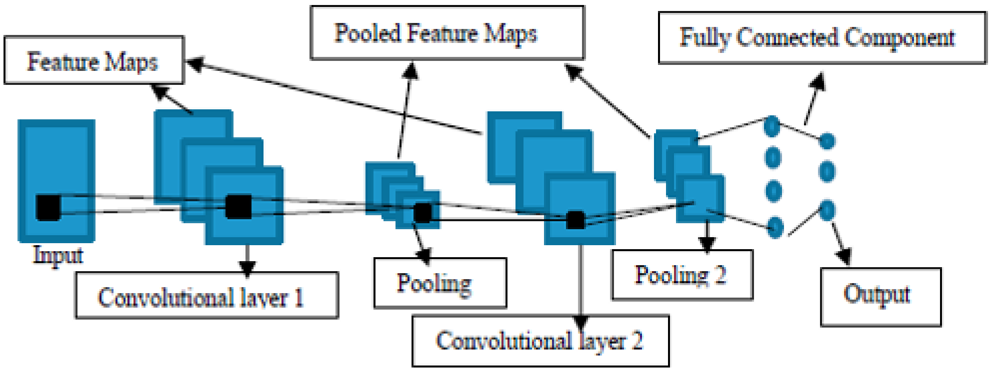

Figure 2 Basic Structure of the model.

CNN Architecture and layers: Convolution Neural Network or CNN is widely used in image processing because of its feature engineering character. It mainly consists of three layers. These are the convolution layer, pooling layer, and completely connected layer. These can be divided into two blocks hidden block and classifier block. The first block consists of a convolution layer with an activation function. This block acts as a feature map. The second layer is a classification that consists of fully connected and SoftMax layers. CNN provides many advantages:

- Segmentation is also done by CNN.
- It is being used for object detection.

Artificial intelligence is a branch of science that helps to make intelligent machines. Many biomedical complicated diseases are using AI for diagnosis. Machine learning is a subset of AI which helps to train a model to perform a specific task. Deep Neural network, Artificial Neural Network is again a subset of Machine Learning. Deep Learning techniques are getting popular now-a-days because it primarily focuses on medical Images which are low-cost imaging techniques and abundantly available in hospitals and clinics. Convolution
Neural Network (CNN) is widely used in medical imaging and medical classification task. These helps in image feature extraction which are not apparent in original images. CNN is a very useful feature extractor, so it can be used for lung image classification without complicated and expensive hand-driven feature engineering. CNN can also be used for image processing like histogram analysis, cropping, and contrast enhancement. This helps to increase the accuracy while decreasing the training time, so lung nodules are extracted based on annotations and diagnostic information. DenseNet- MobileNet takes two-point convolution layers and a depth-wise convolution layer which is basically, a depth-wise separable convolution as a whole, called a dense. The accumulated output feature maps generated by a point convolutions in all previous depth-wise separable convolution layers are the input feature maps of depth-wise separable convolution layer. The input feature map in the point convolution layer is the output feature map generated by the depth-wise convolution in the dense block. There is one dense connection, In the DenseNet-MobileNet model, only one input feature map needs to overlay the output feature map. The DenseNet-MobileNet model does not add other transition layers too therefore after separable convolutions; the size of the feature map gets reduced by the depth-wise convolution with stride 2. Finally, global average pooling is applied and connected directly to the output layer of the MobileNet model. Experiments show that the classification accuracy of the global average pre-cooling depth-wise separable convolution with dense connection before the global average pooling is higher. The two-layer depth-wise separable convolution without dense connection and finally the depth-wise separable convolution layer before global average pooling is also densely connected is comparatively less than previous model. We have used CNN-model for ASPERGER SYNDROME classification.

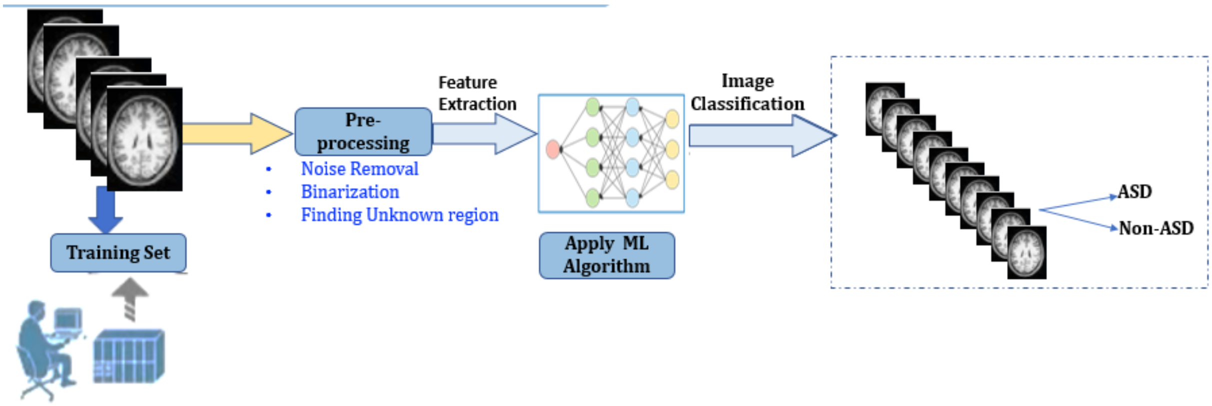

Figure 3 The Workflow diagram.

This research has the following contributions:

1. The main aim of this study is to develop a model facilities imaging technology through screening of MRI of ASPERGER SYNDROME individuals. They lack in need of expert intervention for inference. A machine learning algorithm is trained with ASPERGER SYNDROME patient data such that it can classify between healthy and diseased individuals.
2. Here different deep learning algorithms have been used and performances have been compared for this purpose. A novel dataset has been created for this purpose with ASPERGER SYNDROME individuals of toddler group, children group and adult group.
3. In this work we focus on face dataset generation of ASPERGER SYNDROME toddler, child, adolescent. We present a novel and effective pipeline for generating face dataset from unlabeled and raw data images. There has been more than 70 individuals both girls and boys of different age group.
4. To bridge the data imbalance of ASPERGER SYNDROME kids' vs healthy individuals ACGAN has also been used here. These shows the performances of all algorithms have improved with increased datasets.

Dataset for this research is Version 5 of the Kaggle data set which is publicly available and has 2940 images that are evenly split between two classes: ASPERGER SYNDROME and not ASPERGER SYNDROME. The distribution of male to female pictures in the ASPERGER SYNDROME class is close to 3:1 ABIDE(ASPERGER SYNDROME Brain Imaging Data Exchange) Dataset 1 contains 1112 dataset, including 539 from individuals with ASPERGER SYNDROME and 573 from typical controls ages 7-64 years. The decision to develop the dataset on these datasets is driven by the fact that all of them are open-sourced and completely available to the public and research communities. All datasets are merged together and duplicate images are removed. The inputs are all uniquely identifies using hashing method. The most striking trend is the limited number of cases and scarcity of availability of MRI images associated with ASPERGER SYNDROME patient's data in the public domain. The image pre-processing steps involved are resizing (112 X 112 X 3) and each image is normalized by rescaling the pixels from [0, 255] to [0, 1]. Adaptive Moment Estimation called Adam (Adam is a method for stochastic optimization which calculates adaptive learning rates for parameters.) is used as the optimizer and categorical cross entropy as the loss function. The activation function is ReLU.

The hyper parameters used for training are learning rate = 0.001, and batch size = 16.

The network is trained for 25 epochs and after training, 85.4 per cent accuracy is achieved. The Table 2 contains all the attribute details of the referred novel dataset.

Table 2: attributes in the dataset.

Attribute Id	Attribute Description
1	Patient Age
2	Sex
3	Nationality
4	Patient suffered from any disease during birth
5	Any family member suffered from mental disorder
6	Screening of ASPERGER SYNDROME done by the user before?
7	Screening test type
8	Based on screening method answer 10 questions
9	Screening Score

The novel dataset has the above mentioned common attributes that are used for prediction. Pre-processing of data is done first on the acquired dataset as the real world data contains much error and are often incomplete to meaningful and understandable format. Some of the pre-processing techniques are outlier detection, data discretization, data reduction etc. he distribution of data is 80% for training and 20% for testing datasets. The training dataset is further divided into two parts: training and validation with 80% and 20% data distribution.

4. RESULT AND DISCUSSION

Generative Adversarial Networks (GANs) is based on game-theory where two neural networks are utilized to compete with each other to create new virtual instances of data that can be transmitted as real data. GANs are extensively used for image generation. GAN to perform data augmentation. GANs generate high-resolution samples from highly variable data sets. The Forward GAN which generates diverse images and Backward GAN which generates realistic image and acts as a noise reducer. So basically, in a ACGAN we have an input noise to the generator along with input image which helps the generator to learn the features of brain. The output of a generator is a fake image which is given as an input to the discriminator. Finally, the discriminator classifies between a real and fake image. The discriminator D gives a distribution of probability over class labels and sources. P(S I X); P(C I X) = D(X): The log-likelihood of source class Ls and correct class
Lc forms the objective function. Lc = E[log P(C = c I Xreal)] +E[log P(C = c I Xfake)] (1)
Ls = E[log P(S = real I Xreal)]+E[log P(S = fake I Xfake)] (2) D maximizes Ls + Lc and
G maximizes Lc - Ls.
We propose a GAN architecture based on DCGAN, to produces images which helped the classification network to get trained properly. 100-dimension image is converted to a 64 X 64-pixel image by stride convolutions. The discriminator along with generator plays a mini-max game, where discriminator is trained to distinguish between real and fake image generated by the generator. To evaluate the performance of our model we used a 10-fold cross validation. During training the datasets is randomly partitioned into 10 equal sized subsamples.

1. Dataset 1 + MobileNet

2. Dataset 1 + DenseNet 121
3. Dataset 2 + DenseNet 121
4. Dataset 3 + DenseNet 121
5. Dataset 4 + DenseNet 121
6. Dataset 5 + DenseNet 121
7. Dataset 6 + DenseNet 121
8. Dataset 7 + DenseNet 121
9. Dataset 2 + Dataset 5 + MobileNet
10. Dataset 2 + Dataset 6 + MobileNet.

With the experimentalresults we found that the model gives better accuracy with increased dataset. Here we getthe output of identification of unknow region and also classification model results. However,there is a drawback of GAN we found while performing this experiment. The data generatedby GAN are not as realistic as traditional data augmentation methods. On increasingthe training sample more realistic images are generated. Now, we analyze the effect ofthe data augmentation technique used for ASPERGER SYNDROME detection. The DenseNet-MobileNetarchitecture was used initially, to perform ASPERGER SYNDROME detection. Then to improve the performance we used the synthetic data augmentation technique.
We found that synthetic data augments produced enhanced the performance of CNN. The implementation of the architecture is done using Keras [56] deep learning library in Colab.
There is some limitation of this study
• Architecture can be improved further based on more available database.
• The dataset is obtained from various sources and cross-centre validations were not conducted in this analysis.

Table3: Overall Result of ASPERGER SYNDROME Screening Data

Classifier	Specificity	Sensitivity	Accuracy
Densenet-121	1.0	0.9677	98.30
MobileNet-v2	0.9642	0.8064	88.13
Inception v3	1.0	0.97	98.30
Resnet-51	0.99	0.95	96.43
VGG 16	0.9642	0.9354	94.91

This chart shows the performance of different architectures (Densenet-121, MobileNet-v2, Inception v3, Resnet-51, VGG-16) on the same dataset.
We have made every effort to ensure that the data collected is correctly labelled. Any mistake in data labelling, however, would probably affect the results reported. Many researchers have come up with technological innovations through novel imaging modalities to bridge the gap between the need and the possible care. The lack of existing infrastructure, expert manpower, and awareness about ASPERGER SYNDROME accentuate the occurrence rate across the nation. Eventually, this suffices the market opportunity of Radiological treatment through imaging devices, pharmaceuticals, and therapeutics. Top diagnostic imaging device manufacturers are ready to invest to get a better diagnosis. Although several imaging technologies that are enforcing the market towards point-of-care and real-time implementation through screening of pulmonary conditions, they lack in need of expert intervention for inference (i.e. unable to provide functional characterization through an AI-driven computational platform). With our proposed invention, we aim to dilute the shortcomings of the existing solutions to embody point-of-care and real-time facilities through an AI-driven computational module with reduced expert intervention. Therefore, we also anticipate a very good

scope of industrial application with the present market demand and crisis in the existing healthcare framework. Some work of image analysis through computational modelling has been carried out for detecting various diseases. Preliminary work has been conducted using a deep neural network approach to scale up the radiological rapid screen of symptomatic subjects.

Table 4: Overall Result of ASPERGER SYNDROME Screening Data with increased datasets

Classifier	Specificity	Sensitivity	Accuracy
Densenet-121	0.9787	0.9757	97.64
MobileNet-v2	0.9148	0.9696	95.11
Inception v3	1.0	0.9939	99.53
Resnet-51	0.9575	0.9696	96.43
VGG 16	0.9574	0.8888	98.11

The study shows that performance of the architecture increases with increased dataset. The data imbalances are addressed by ACGAN. This helps in improving the performance of architecture. Studies have revealed that in certain scenarios when doctors failed to diagnose a disease a deep learning Algorithm performed wonderfully.

• We can implement this software in hospitals and clinics for getting better results.

• Convolution Neural Network has been used here, so feature extraction is not required.

We can also avoid complicated and expensive feature engineering. With our proposed research, we aim to dilute the shortcomings of the existing solutions to embody fast and real-time facilities through an AI-driven computational module with reduced expert intervention.

5. CONCLUSION

In our study we have shown early detection of ASPERGER SYNDROME using various architectures of machine learning and deep learning. The dataset contains data of kids, toddler and adult non-clinical datasets. Performance evaluation metric was used to evaluate performances of various architecture models of machine learning and deep learning on the mentioned dataset. Our long-term goal is to produce a clinically-useful classifier than can perform high-accuracy differential diagnosis using brain imaging data. As such, the classifier reported here might not be directly useful for clinicians; however, our approach does provide important results in the basic science of inferring clinical information about individual patients from brain imaging data. The results strongly suggest that performance of Inception v3 is good and performance of VGG-16 increases immensely on increased datasets.
The critical step, as it demonstrates the potential of this machine learning approach.

1. A limitation of this work is the quantity of data available, particularly for ASPERGER SYNDROME.
2. The decision for each child must be independently confirmed by an experienced mental health specialist in a clinical setting.
3. We can define better model to select features, which are well-known for object detection, and show they can be useful for classification of psychiatric illnesses using brain images. If we can successfully apply our method to learn classifiers

from two large multi-site datasets, we expect that our approach will also be able to produce tools that can effectively classify other psychiatric disorders, from structural and functional MRI data, and hope that this will lead to extensions that are clinically relevant for various diseases.

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