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Deep Learning Approach to Predict Autism Spectrum Disorder (ASD)

[1]V. Lokesh Raju, [2]B. Aishwarya, [3]V. Praveen Kumar, [4]K. Anil Kumar, [5]P. Nithish Reddy, [1]*M. Jayanthi Rao

Department of Computer Science and Engineering, Aditya Institute of Technology and Management, Tekkali-532201, India,

[1]*corresponding Author mail: jayanth.mtech@gmail.com

Abstract

Autism Spectrum Disorder (ASD) is a one type of neuro-disorder. Due to this disease a person behaviour is being changed while they make interaction and communication with others. Autism Spectrum Disorder (ASD) is also called as “Behavioural Disease”. If a person is being effected from ASD, Symptoms are usually identified in the first two years of their life. According to so many researches and studies ASD problem is starts with childhood and continues to keep going throughout their life. Recent studies proven that ASD is gaining it’s momentum and growing faster than ever. So it makes somewhat expensive and time taken in finding out autism symptoms through screening tests. With the advancement of Deep Learning Techniques, we planned to work on ASD and propose a methodology in deep learning for earlier prediction of ASD.

In this project work we are going to work with some of the Deep Learning Algorithms and also with some of the Advanced Machine Learning Techniques. Our project aim is to find out the best algorithm fit for early prediction of ASD based on performance metrics like Accuracy, Precision Score, Recall Score and F1 Score. For this project work we get the dataset from Kaggle repository, which consists of 21 attributes and 704 records. All considered algorithms have been implemented on python-programming using Spyder IDE with some important packages and libraries like pandas, numpy, matplotlib, sklearn and seaborns.

Keywords: Autism Spectrum Disorder (ASD); 1D - Convolutional neural network (CNN); Artificial Neural Network (ANN); Decision Tree Classifier (DT), Naïve Bayes Classifier (NB), Logistic Regression (LR); Support Vector Machine (SVM);

1. Introduction

Autism Spectrum Disorder (ASD) is a neuro-disorder. A person who is suffering from the Autism Spectrum Disorder is not able to do social interaction and communication with others. In this, a person’s life is usually affected for lifetime. The causing factors for this disease is both environmental and genetic factors. The symptoms of this problem may be started at the age of three years and may continue for the whole life. It is not possible to completely treat the patient suffering from this disease, if the symptoms are early detected its effects can be reduced for some time. By assuming that human genes are responsible for it, scientists yet not recognized the exact cause of ASD. The human genes affect the development by influencing the environment. There are some factors which influence ASD like as low birth weight, a sibling with ASD and having old parents, etc. Instead of this, there are some social interaction and communication problems like as:

• Inappropriate laughing and giggling
• Insensitivity of pain
• No proper eye contact
• Improper response to sound
• May not have a wish for cuddling
• Unable to express their gestures

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• No proper interaction with others
• Want to live alone
• Using echo words etc.

People with ASD also have difficulty with interests and constantly repetition of behaviors. The following list presents specific examples of the types of behaviors.

• Repeating certain behaviors like repeating words or phrases most time.
• The Person will be upset when a routine is going to change.
• Having a little interest in certain matters of the topic like numbers, facts, etc.
• Less sensitive than other person in some cases like light, noise, etc.

The problem of autism spectrum disorder (ASD) have been increasing nowadays among all ages of the people. Early detection of this neurological disease can greatly assist in the maintenance of the mental and physical health. With the deep learning-based models in the predictions of various human diseases, the early detection based on various health and physiological parameter now seems possible. This factor motivated us to increase interest in the detection and analysis of ASD diseases to improve better treatment methodology.

2. Literature Survey

Several Studies have made use of Machine Learning in various ways to improve and speedup the diagnosis of ASD. In this paper Raj, suman, et al. [1] made an attempt to explore the possibility to use Naïve Bayes, SVM, Logistic Regression ,KNN ,Neural Network and CNN for predicting and analysis of ASD problems in child, adolescents and adults. The proposed techniques are evaluated on publicly available three different non-clinically ASD datasets. First dataset related to ASD screening in children has 292 instances and 21 attributes. Second dataset related to ASD screening Adult subjects contains a total of 704 instances and 21 attributes. Third dataset related to ASD screening in Adolescent subjects comprises of 104 instances and 21 attributes. After applying various machine learning techniques and handling missing values, results strongly suggest that CNN based prediction models work better on all these datasets with higher accuracy of 99.53%, 98.30%, 96.88% for ASD Screening in Data for Adult, Children, and Adolescents respectively.

Heinsfeld, Anibal Sólon, et al. [2] have investigated ASD patients brain imaging data from a world-wide multi-site database known as ABIDE (Autism Brain Imaging Data Exchange). According to recent Centers for Disease Control data, ASD affects one in 68 children in the United States. The first goal of the present study was to classify autism spectrum disorder (ASD) and control participants based on their respective neural patterns of functional connectivity using resting state functional magnetic resonance imaging (rs-fMRI) data. Studies that applied ML algorithms to ASD brain imaging data have classified individuals as autistic or control from their fMRI brain activation with up to 97% accuracy . In another study of ASD participants it obtained a 76.67% classification accuracy. Supervised learning methods, such as support vector machine (SVM) or Gaussian naive Bayes (GNB) classifiers. Deep models allowed for better results (mean accuracy of 50.74%) compared to supervised learning methods (mean accuracy of 47.97%) such as Linear Regression and SVM.

Vakadkar, Kaushik, et al. [3] have applied models such as Support Vector Machines (SVM), Random Forest Classifier (RFC), Naïve Bayes (NB), Logistic Regression (LR), and KNN to the dataset and constructed predictive models based on the outcome. The accuracies for the LR is 97.15%, NB is 94.70%, SVM is 93.84%, KNN is 90.52% and RFC is 81.52% respectively. And also plan to employ deep learning techniques that integrate CNNs and classification to improve robustness and overall performance of the system. The analysis of these classification models can be used by other researchers as a basis for further exploring this dataset or other ASD data sets.

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Ke, Fengkai, et al. [4] have investigated the structural and strategic bases of ASD using 14 different types of models, including convolutional and recurrent neural networks. Using an open source autism dataset consisting of more than 1000 MRI scan images and a high-resolution structural MRI dataset, we demonstrated how deep neural networks could be used as tools for diagnosing and analyzing psychiatric disorders. We trained 3D convolutional neural networks to visualize combinations of brain regions, thus representing the most referred-to regions used by the model whilst classifying the images.

Subah, Faria Zarin, et al. [5] have propose an ASD detection model using functional connectivity features of resting-state fMRI data. Our proposed model utilizes two commonly used brain atlases, Craddock 200 (CC200) and Automated Anatomical Labelling (AAL), and two rarely used atlases Bootstrap Analysis of Stable Clusters (BASC) and Power. A deep neural network (DNN) classifier is used to perform the classification task. The mean accuracy of the proposed model was 88%, whereas the mean accuracy of the state-of-the-art methods ranged from 67% to 85%. The sensitivity, F1-score, and area under receiver operating characteristic curve (AUC) score of the proposed model were 90%, 87%, and 96%, respectively. Comparative analysis on various scoring strategies show the superiority of BASC atlas over other aforementioned atlases in classifying ASD and control.

Karunakaran, P., et al. [6] believed in better visualization and classification of neuro images in early month captures and appended of MSEL. fMRI is one of the controlling tools for measuring non-invasively measure brain activity and it provides with good resolution. For high resolution of brain activity, fMRI gives better than electro encephalon graph (EEG). The linear regression based algorithms are predicted in coronal slice of scanned image as “autistic” function after computed the feature of thicker cortex and more folds in the image. Our method is providing good effects in higher level aspects of cognition as early prediction during decision, valuation, control (DVC) and social interactions. The early prediction results highlight that MSEL is useful technique to predict autism in a high accuracy. Our integrated SVM algorithm is suitable and effective in high dimensional space.

Akter, Tania, et al. [7] applied several feature transformation methods, including log, Z-score and sine functions to these datasets. We found SVM showed the best performance for the toddler dataset, while Adaboost gave the best results for the children dataset, Glmboost for the adolescent and Adaboost for the adult datasets. After these analyses, several feature selection techniques were used with these Z-score-transformed datasets to identify the significant ASD risk factors for the toddler, child, adolescent and adult subjects. The results of these analytical approaches indicates, when appropriately optimised, machine learning methods can provide good predictions of ASD status.

Xu, Lingyu, et al. [8] had explored the possibility of using a multilayer ANN for the classification between children with ASD and typically developing (TD) children based on short-time spontaneous hemodynamic fluctuations. To perform feature extraction and classification, CGRNN was used which combined a CNN and GRU, since CGRNN has a strong ability in finding characteristic features and acquiring intrinsic relationship in time series. For the training and predicting, short-time (7 s) time-series raw fNIRS signals were used as the input of the network. By using this combined deep-learning network, a high accurate classification between ASD and TD could be achieved even with a single optical channel, e.g., 92.2% accuracy, 85.0% sensitivity, and 99.4% specificity. CGRNN can identify characteristic features associated with ASD even in a short-time spontaneous hemodynamic fluctuation from a single optical channel, and provide highly accurate prediction in ASD.

Xu, Lingyu, et al. [9] have 25 ASD children and 22 TD children were measured with functional near-infrared spectroscopy located on the inferior frontal gyrus and temporal lobe. To extract features used to classify ASD and TD, a multi-layer neural network was applied, combining with a three-layer CNN and a layer of LSTM with Attention mechanism. The fNIRS time series were then obtained and used as the input

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of the multi-layer neural network. A good classification between ASD and TD was obtained with considerably high accuracy by using a multi-layer neural network in different brain regions, especially in the left temporal lobe, where sensitivity of 90.6% and specificity of 97.5% achieved. The ‘‘CLAttention” multi-layer neural network has the potential to excavate more meaningful features to distinguish between ASD and TD.

Alteneiji, Maitha Rashid, et al. [10] have applied models like SVM, XgBoost, AdaBoost, CV Boosting, Neural Network, Random Forest, Naïve Bayes, Random Forest- GBM. The accuracies of the models of the child, adolescent and toddler database are SVM (95.41%, 91.89% and 96.83%) XgBoost (92.07%, 75.51% and 97.14%) AdaBoost (90.13%, 93.24% and 94.60%) CV Boosting (92.73084, 82.37096 and 94.68691) Neural Network (96.73%, 96.10% and 99.03%) Random Forest (87.33%, 88.60% and 94.24%) Naïve Bayes (92.53%, 94.75% and 94.59%) Random Forest- GBM (93.33%, 93.67% and 95.84%). The toddler database, adolescent and child databases using the Neural Network model also have excellent accuracy results compared with the machine learning models used in this paper concerning predictive power, sensitivity, and specificity.

Tyagi, Bhawana, et al. [11] have taken the data of adult people from the age of 17 to 60 years and tried to diagnose the Autism Spectrum Disorder by applying data mining techniques. There is ample range of questions in the dataset that was used in our research. The KNN, SVM, LR , CART , Naïve Bayes and LDA algorithms have been used in the classification. Here we convert the data of some attributes into the numerical values. In the result of Our implementation the Linear Discriminant Analysis algorithm shows the best result i.e., 72.2024% and most accurate than other algorithms.

Küpper, Charlotte, et al. [12] have expand on this work with a specific focus on adolescents and adults as assessed with the ADOS Module 4. We used a machine learning algorithm (support vector machine) to examine whether ASD detection can be improved by identifying a subset of behavioral features from the ADOS Module 4 in a routine clinical sample of N=673 high-functioning adolescents and adults with ASD (n=385) and individuals with suspected ASD but other best-estimate or no psychiatric diagnoses (n=288).

3. Dataset

Dataset for this research purpose has been collected from the Kaggle Repository which is publicly available. The detailed summary of the dataset is shown below:

Table 1: List of ASD datasets

SI. No.	Dataset Name	Sources	Attribute Type	Number of Attributes	Number of Instances
1	ASD Screening Data for Adult	Kaggle Repository	Categorical, continuous and binary	21	704

These datasets have 21 attributes that are used for prediction. These attributes are listed below:

Table 2: List of Attributes in the dataset

Attribute Id	Attributes Description
1 - 10	Based on the screening method answers of 10 questions
11	Age of the Adult
12	Gender of the adult

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13	Ethnicity
14	Jundice Score
15	Austim Score
16	Country Of Residence
17	Used any Screening Application or Not
18	Resullt of Particular Screening
19	Age Description
20	Type of Relation
21	Screening Score

4. Proposed Methodology

Figure 1 shows the steps in the proposed workflow which involves the pre-processing of data, training, and testing with specified models, evaluation of results and prediction of ASD. This work is implemented in Python 3.

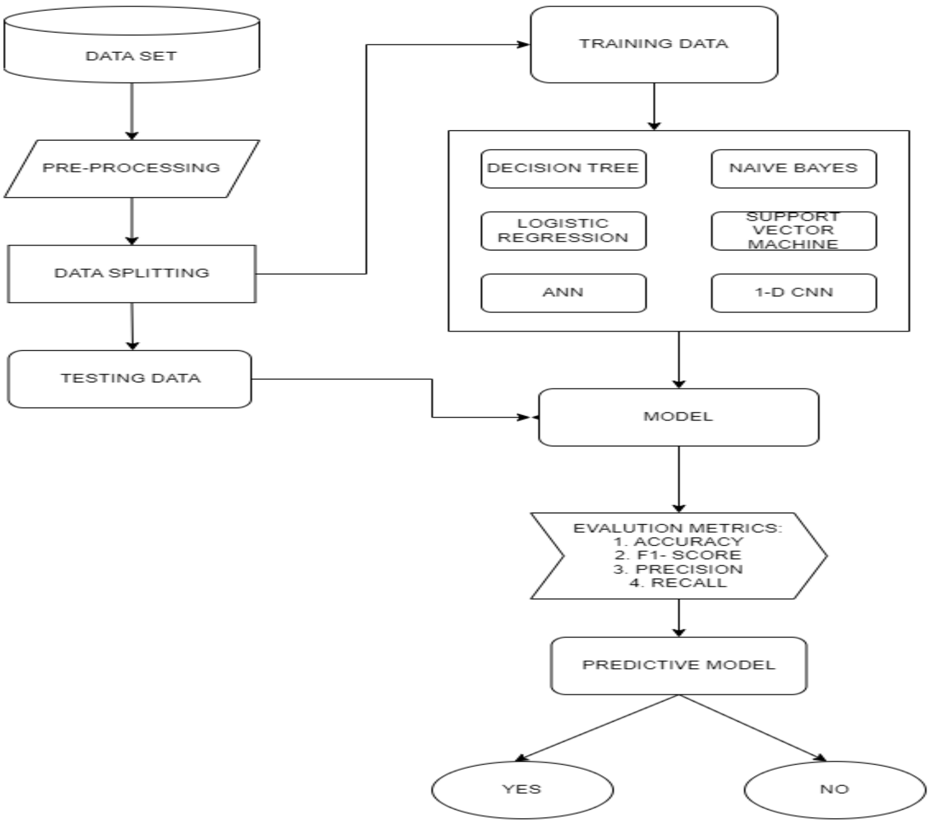

Figure. 1. Architecture of the model involved in ASD prediction.

4.1. Data Pre-Processing

Data pre-processing is a technique in which transform the raw data into a meaningful and understandable format. Real-world data is commonly incomplete and inconsistent because it contains lots of errors and null values. A good pre-processed data always yields to a good result. Various Data pre-processing methods are used to handle incomplete and inconsistent data like as handling missing values, outlier detection, data discretization, data reduction (dimension and numerosity reduction), etc. The problems of missing values in

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these dataset has been handled by imputation method, after pre- processing on training data we are applying different machine learning and deep learning algorithms[13-16]

4.2. Training and Testing Model

The whole dataset has been split into two parts i.e. one part is training the dataset and the other one is testing dataset with a ratio of 70:30 respectively. Figure 2 shows the final training, testing and validation sets on which classification has been performed.

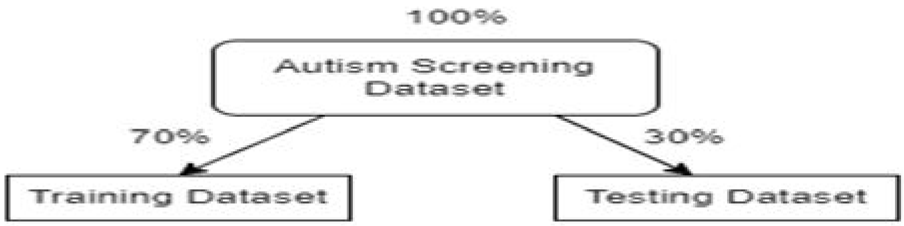

Figure. 2. Final Training, Testing and Validation Sets

4.2.1 Decision Tree Classifier

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome**.** In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node**.** Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.

4.2.2 Naive Bayes

A naive Bayes classifier is a supervised learning algorithm. It is a generative model and is based on joint probability distribution. The Naive Bayes concept based on independence assumptions. It exhibits less training time as compared to SVM and ME model. It calculates the posterior probability for a dataset using the prior probability and likelihood.

$$P(A|B)=(P(B|A)P(A))/P(B)$$

P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.

P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.

P(A) is Prior Probability: Probability of hypothesis before observing the evidence.

P(B) is Marginal Probability: Probability of Evidence

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4.2.3 Logistic Regression

LR is a regression tool that is used to analyse the binary dependent variables. Its output value lies in either the 0 or 1 form. It is used for the continuous value dataset. It tells the relationship between one dependent binary variable, and one nominal or ordinary variable. It can be represented by the sigmoidal function.

4.2.4 Support Vector Machine (SVM)

SVM is a linear supervised machine learning approach that is used for classification and regression. It is a pattern recognition problem solver. It does not cause the problem of overfitting. SVM separates the classes by defining a decision boundary[19].

4.2.5 Convolution Neural Network (CNN)

CNN is one of the deep learning techniques known to build models for various problems. It is a feed-forward neural network that is inspired by the human brain. A CNN model contains one input layer, one output layer, and many other different layers i.e. convolution layers, max pooling, fully connected layers, and normalization layers. Their activation functions can be computed with Matrix Multiplication, which is followed by a bias offset. A simple diagram of CNN is given below:

4.2.6 Artificial Neural Network

ANN is a neural network that has a connection with multiple neurons. Each neuron cell having a group of input values and associated weights. The most common artificial 0 neural network feeds forward neural network. In this network, the flow of information moves in the only forward direction. This type of network contains three main layers, first is the input layer, the second is a hidden layer and last is the output layer. There is no cycle or loop in the network.

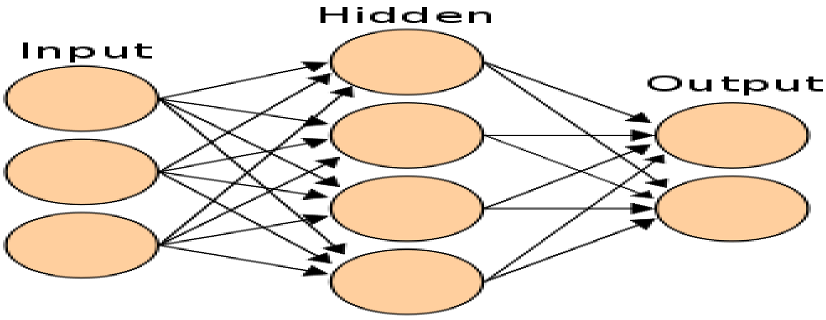

Figure. 5. Artificial Neural Network

5. Result and Discussion

The result is measured in terms of Accuracy, F1- Score, Precision Score and Recall Score by using the confusion matrix and classification report. The result depends on how accurate the model is trained.

Performance Evaluation metrics

Measuring performance is key to check how well a classification model work to achieve a target. Performance evaluation metrics are used to evaluate the effectiveness and performance of the classification model on the test dataset. It is important to choose the correct metrics to evaluate the model performance such as confusion matrix, accuracy, specificity, sensitivity, etc. Following formulas are used to find the performance metrics:

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Table 3: Elements of a Confusion Matrix

	Predictive ASD values	
Actual ASD values	True positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)

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

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

$$\text{F1- Score} = \frac{TP}{TP+1/2(FP+FN)}$$

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

Experimental results of various machine learning and deep learning algorithms approach with all features selection have been shown for ASD screening data for Adults. In this, all 21 features are selected to find the precision, F1-Score, Recall and accuracy of the predicted model. For the implementation of Naïve Bias algorithm Gaussian NB has been used. For SVM Kernel has been used with 0.1 gamma value. In ANN, Adam Optimizer ,100 epoch and binary cross-entropy loss function has been used. In CNN, Relu activation Function, Adam Optimizer, binary cross-entropy loss function, 16 & 32 filters and 0.5 dropouts with 100 epoch has been used. The Overall performance measures of all machine learning and deep learning classifiers with the mentioned dataset have been shown below in details:

Table 4: Overall Results for Autistic Spectrum Disorder Screening Data for Adult Using Machine Learning Algorithms

Classifier	**Precision Score**	**Recall Score**	**F1- Score**	**Training Accuracy**	**Testing Accuracy**
Decision Tree Classifier	89.32	97.35	93.16	100	92.96
Naïve Bayes Classifier	82.01	82.01	82.01	85.23	82.29
Logistic regression	81.15	82.01	81.57	87.02	81.77
Support Vector Machine	85.27	88.88	87.04	92.05	86.79

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Evaluation of various machine learning models on ASD adult diagnosis dataset observed an accuracy in the range of (81.77% to 92.96 %) on the original dataset. Logistic Regression with 1000 iterations has produced the least accuracy of 81.77%. Decision Tree Classifier produced 92.96 % prediction accuracy on the original dataset. The confusion matrixes of all Machine Learning algorithms also describe the results of the prediction model.

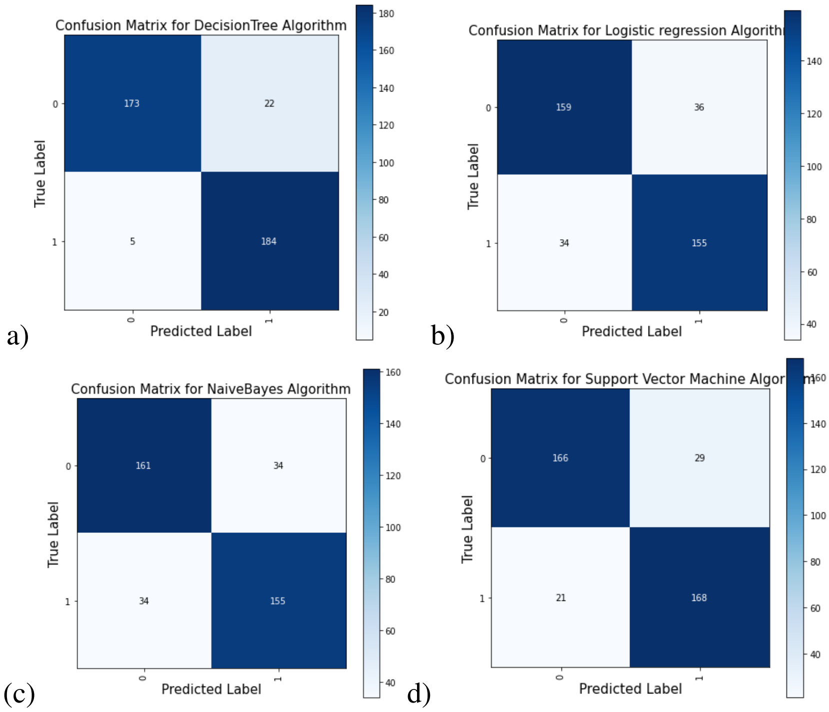
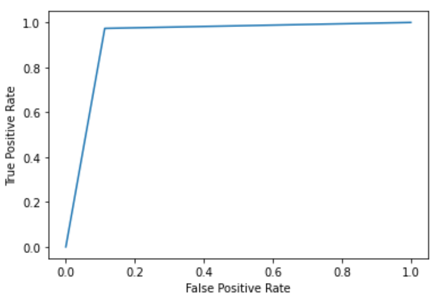
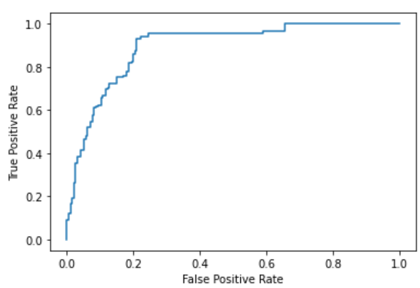


Figure 6: Confusion Matrices for Different Machine Learning Algorithms

The above mentioned Machine Learning algorithms are also compared with AUC Curves and ROC values. Below Showing Figures are the representation of AUC curves of Decision Tree Classifier, Logistic Regression, Naïve Bayes Classifier and Support Vector Machine.



a) Decision Tree Classifier



b) Logistic Regression

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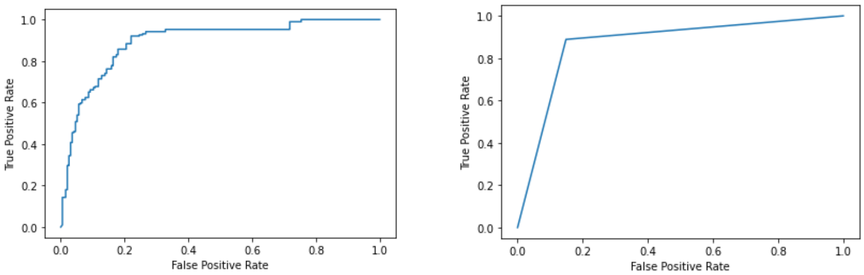

c) Naive Bayes Classifier d) Support vector Machine

Fig 7: ROC Curves for Machine Learning Algorithms.

Classifier	ROC Score
Decision Tree	93.03
Logistic Regression	89.47
Naive Bayes	89.32
Support Vector Machine	87.00

Comparision of various machine learning algorithms can be done by ploting a bar plot. Below mentioned bar plot will show case the comparision among algorithms, based on that it can be easy for us to conclude a best fit algorithm for our proposed work.

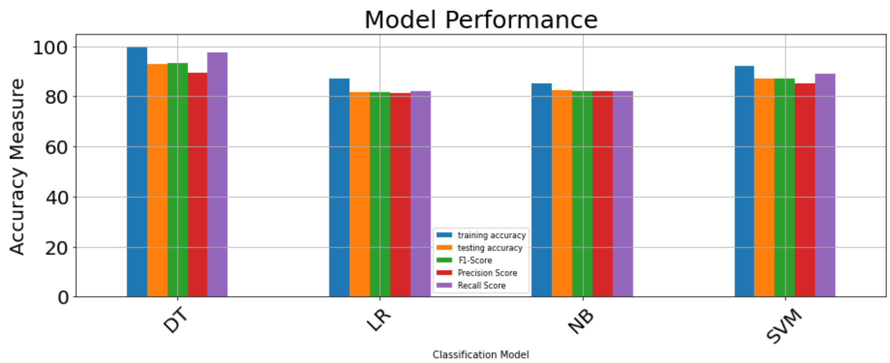

Fig 8: Bar Plot for Various Machine Learning algorithms

Deep Learning Algorithms:

When our dataset is applied on various deep learning algorithms like Artificial Neural Network (ANN) and One Dimensional Convolutional Neural Network (1D-CNN) those algorithms are performed well and produced high accuracies compared to machine learning algorithms.

Training Accuracy and Testing Accuracy Comparision of Machine Learning and Deep Learning Algorithms are shown in below Figure:

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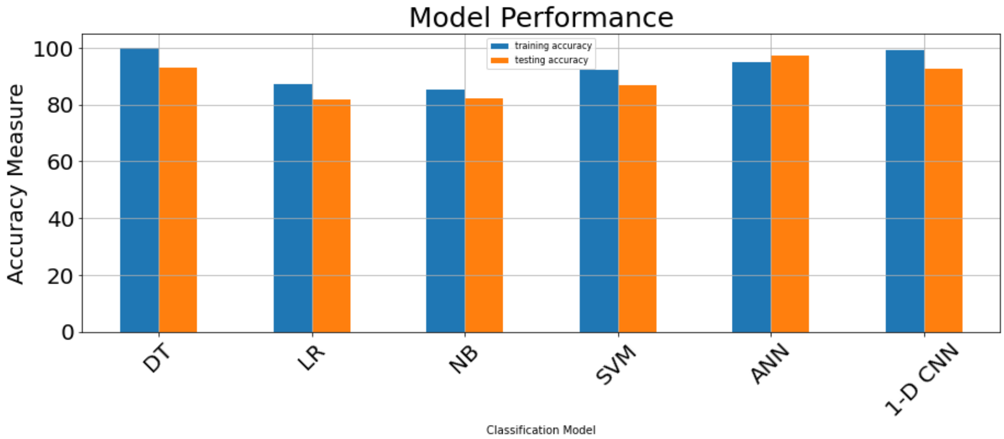

Fig 9: Bar plot for comparision of Training and Testing Accuracies of Machine Learning and Deep Learning Algorithms

Mostly when we declare any model is performing well in that case we gone to conclude it with testing accuracy of thet particular model. Below figure show the testing accuracy comparision of Various Deep – Learning Algorithms with Machine Learning Algorithms:

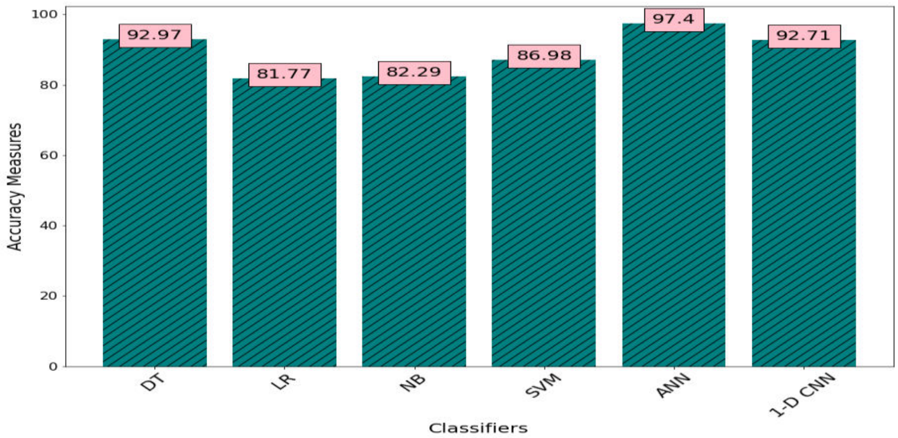

Fig 10: Bar Plot for comparision of Testing accuracy for Machine and Deep Learning Algorithms.

6. Conclusion

In this work, detection of Autism Spectrum Disorder was attempted using various machine learning and deep learning techniques. Various performance evaluation metrics were used to analyze the performance of the models implemented for ASD detection on non-clinical dataseti.e Adult Screening Dataset. When we compare results between machine learning and deep learning algorithms in those deep learning algorithms are performing well. Mainly Artificial neural network in some cases perform very well and produce upto 99% accuracy. Likely 1D CNN also perform very well when it compare with other machine learning algorithms and gives upto 93% accuracy.

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