A Stack Based Ensemble Learning Method for Diagnosing Autism Spectrum Disorder

Lavanya Kampa[1]
Associate Professor
Department of Information Technology, Lakireddy Bali Reddy College of Engineering, India.
dr.lavanyakampa@gmail.com
Kethe Yamini[2] **Amani Basavaraju**[3] **Kotagiri Anoop**[4]
Student
Department of Information Technology, Lakireddy Bali Reddy College of Engineering, India.
kethe.yamini543@gmail.com
amani160102@gmail.com
anoopkr0027@gmail.com

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Abstract

Autism Spectrum Disorder (ASD) is a spectrum of neurodevelopment impairments that affects the nervous system and also affects individual's over all cognitive, emotional, social, and physical health. This disorder can be observed at early stages of life. In developmental stages, i.e., within the first two years after birth its symptoms are usually shown. The only approach for diagnosing ASD is using through Clinical standardized tests. This not only necessitates a longer diagnosis time, but it also results in a significant rise in medical costs. To improve the precision and time required for diagnosis, single machine learning techniques are being used now days but these are not sufficient for effective prediction of ASD. In this study, introduced an ASD prediction model for children dataset using Stack ensemble learning approach and which complements to the conventional single learning methods. In this study ASD predictive analysis is done in three stages. At first stage, applied feature selection method i.e., Principal Component Analysis (PCA) to retrieve optimal features of children data set. Later, in second stage, ASD is diagnosis with predictive model is designed using various base classification techniques which includes Random Forest Classifier (RFC), Naïve Bayes (NB), and Logistic Regression (LR) to children dataset. At the last stage, to improve the performance of ASD prediction model, applied stack ensemble learning method with

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mentioned base learners. The results shows that proposed ensemble based predictive model is best for ASD diagnosis for the children dataset at early stages than the base Machine Learning methods in terms of accuracy, precision, Recall and F1- Score.

Keywords: Autism Spectrum Disorder, Principal Component Analysis, Random Forest, Naïve Bayes, and Logistic Regression, and Ensemble Learning.

1. Introduction:

According to WHO, one in every 59 children will have ASD. It is a developmental disability disorder caused by the difference in the brain in terms of structure or function, which is largely acknowledged as the cause for ASD [1-5]. It is important to be recognized early in order to avoid changes in communication, social difficulties, obsessive interests, and repeated behaviors. Although diagnosing autism is challenging, the availability of datasets and the behavior of autistic children might help us anticipate autism at an early stage. According to scientific evidence, many factors, including environmental and genetic factors, increase a child's risk of developing autism. Multiple variables interacting in various ways are most likely to blame for autism (i.e., genes, environment and brain development). It takes time and money to diagnose autism, and getting tested costs time and money. As a result, it is difficult to identify the disorder at early stage for better treatment. In this paper, the research is mainly focused on the children dataset forearly prediction of ASD diagnosis using ensemble learning approach. However, some research study has been done in the field of AI, image processing and Machine Learning to improve the techniques for pre-diagnosis of ASD. To solve the issue, this research work develops a new framework for ASD pre-diagnosis using a stack Ensemble Learner. The complete idea of the proposed model is described in Figure 1.

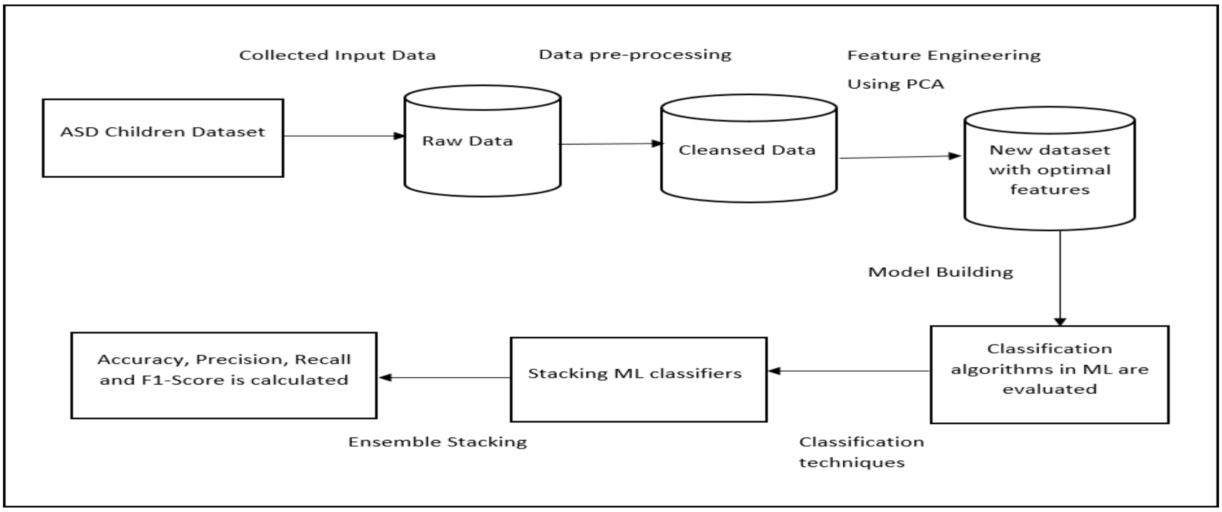

Figure-1: Proposed Model for Classification of ASD

Here in Figure-1, Data Pre-processing is important that includes data cleaning, data transforming. Data cleaning is the approach of handling missing data. Here, in children dataset; missing data is handled using basic ensemble technique i.e., averaging. PCA is a dimensionality reduction technique which maximizes the variance of data [10-14]. Feature engineering is a process of selecting optimal features from the dataset. From the selected features identifying the important principal components. Supervised machine learning methods are used for the process of classifying ASD traits [6-9]. Hence, by using all the above approach we build the model.

An approach that combines a group of learned classifiers chosen from the training dataset, then these learned classifiers are utilized to generate the class of a test data instances based on the individual decisions of these classifiers which improves performance by reducing biased decisions. This approach is popularly known as The Ensemble-based Learning approach [2]. It uses the basic classification algorithms to progressively develop classification models which learns not to disregard the preceding learned models, and not necessary to handle the previously seen training data sets. This ensemble-based approach assures a decision as a group which is sought for the test data class assignment. Some common ensemble learners like Boosting, Stacking and Bagging will be discussed briefly in next section. In this study, an ensemble-based classification model has been proposed and is called Stack Ensemble Classification for Autism pre-diagnosis (SEC_AP). The base classifier for SEC_AP is based on Logistic regression which keeps amending the model's structures and adds them to SEC_AP. This base learning algorithm have good generalization ability which simplifies deriving classifiers for better performance. At first stage, applied preprocessing techniques which includes, data cleaning, data normalization, data exploration, and feature reduction and selection method i.e., Principal Component Analysis(PCA) to retrieve optimal features of children data set. Later, in second stage, ASD is diagnosis with predictive model is designed using various base classification techniques which includes Random Forest Classifier (RFC), Naïve Bayes (NB), and Logistic Regression (LR), Support vector machine (SVM), Decision Tree (DT), KNN to children dataset. At the last stage, to improve the performance of ASD prediction model, applied stack ensemble learning method with mentioned base learners. Among all the classifiers, by stacking Gaussian Naïve Bayes Random Forest our model has best accuracy The results shows that proposed ensemble based predictive model is best for ASD diagnosis for the children and toddler datasets at early stages than the base Machine Learning methods in terms of accuracy, precision, Recall and F1-Score.

The paper is catalogued as follows; Section 2 presents the work on the adaptation of Convolution neural network, Deep learning, and Machine Learning techniques for screening autism at early stage. In Section 3, the methodology of the research is discussed. The results and discussions are discussed in Section 4. Lastly, conclusions and future work are given in Section 5.

2. Related Work

The existing clinical approaches for diagnosing autism are time consuming. In an effort to solve this issue and facilitate a procedure for early detection of autism, Researchers have been working to develop new strategies for preliminary screening methods that use Machine Learning to help with diagnosis of autism disorder in order to tackle this problem and ease early identification of autism in children and toddlers. Also, other areas like fuzzy logic, image processing, deep learning, convolution neural networks and so on were used for diagnosing the traits of autism. Few research conclusions, Identification of high-risk autism on audio and video data under still-face paradigm using support vector machine classifier had accuracy of 90% [3]. As a part, functional magnetic resonance images were constructed into a brain network and the features of autism were defined as eigen values. Using feature selection algorithms, proposed a model which combined all the features of autism syndrome and achieved classification accuracy through Linear Discriminant Analysis-77.7% [4]. In the paper [5], the research done on structural MRI images using deep learning in which several models were build for classifying autism disorder. According to the study [6], a recommendation system was developed using multi classifier regression model. Identifying autism disorder using CNN from the Electroencephalography (EEG) data to classify ASD subjects and normal subjects [7]. proposed a system using to identify children with autism and their abnormal behavioral traits using machine learning. They gave conclusion that the undertaken proof from the concept study that a simple upper-limb action could be useful to meticulously classify autism spectrum disorder (ASD) low functioning children with aged 2-4[8]. XGB, Light GBM, AdaBoost are well performed boosting algorithms which were propagated to overcome the wrong predictions during the class assignment phase and the cost associated with the predictions [9]. They follow an approach by constructing a base classification method, which is chosen from supervised classification algorithms and using some initial classifier. Then, the initial classifier will then be used to classify the training dataset to reduce bad classified data and a new weight will be assigned to the each wrongly classified training data. After the training instances have been assigned with new weights, then a new classifier is constructed from the revised training dataset and the procedure is repeated until there is no further advancement can be attained in terms of predictive accuracy. Finally, whenever a test data is set for prediction, then models learned with different data weights are utilised to collectively determine and decide its class. Many ML techniques to identify ASD traits like delay in development of brain structure, obesity, less physical activities in children experimented using naive Bayes, SVM and random forest algorithm and compared those results. Wall et al. had research on classifying autism using short screening test validation and gave an overview that the AD Tree and the functional tree had performed well with high sensitivity, specificity and accuracy [10]. We had research on autism disorder using deep learning algorithm and neural network utilising a large brain imaging dataset from the Autism Imaging Data Exchange (ABIDE I) to identify ASD patients, and achieved a mean classification accuracy of 70%, with an accuracy range of 66% to 71%. The random forest classifier had a mean accuracy of 63%, whereas the SVM classifier had a mean accuracy of 65%. [11] [13-15].

3. Methods and Material

Many research studies have reported on the success of using an effective application of intelligent machine learning algorithms in identifying and forecasting ASD disorders. This section describes about the core machine learning algorithm which support for the pre-diagnosis of ASD child care. The study which introduces the Ensemble Learning to diagnose ASD in early stages and described detail in Figure 1. The objective of this study is to improve the speed and accuracy ofdiagnosis of ASD in child care in early stage and used new meta-level stacking learning. A technique that enables researchers to combine multiple distinct prediction algorithms to a combination of an algorithm known as Stack generalization [19-21].

3.1. Data preprocessing

During the analysis stage pre-classification done based on few of the important variables like age, gender, autism, and jaundice is shown in Figure 2 and Figure 3. Finally, 70% of the data is selected for training, and 30% of the data is for testing. Here, Data Pre-processing in the figure-1 includes data cleaning, data transforming. Data cleaning is the approach of handling missing data. Here, in children dataset missing data is handled using basic ensemble technique i.e.., averaging. Age attribute missing data handledusing averaging method. All other attributes missing data handled using ffill method from the panda's library. Using various methods from simple imputer function the input data is being transformed. Feature engineering is a process of selecting optimal features from the dataset. Using the concept of correlation, most important featured attributes are selected. From theselected features identifying the important principal component. Hence, by using all the above approach dimensions are reduced and the input data is ready for building the model.

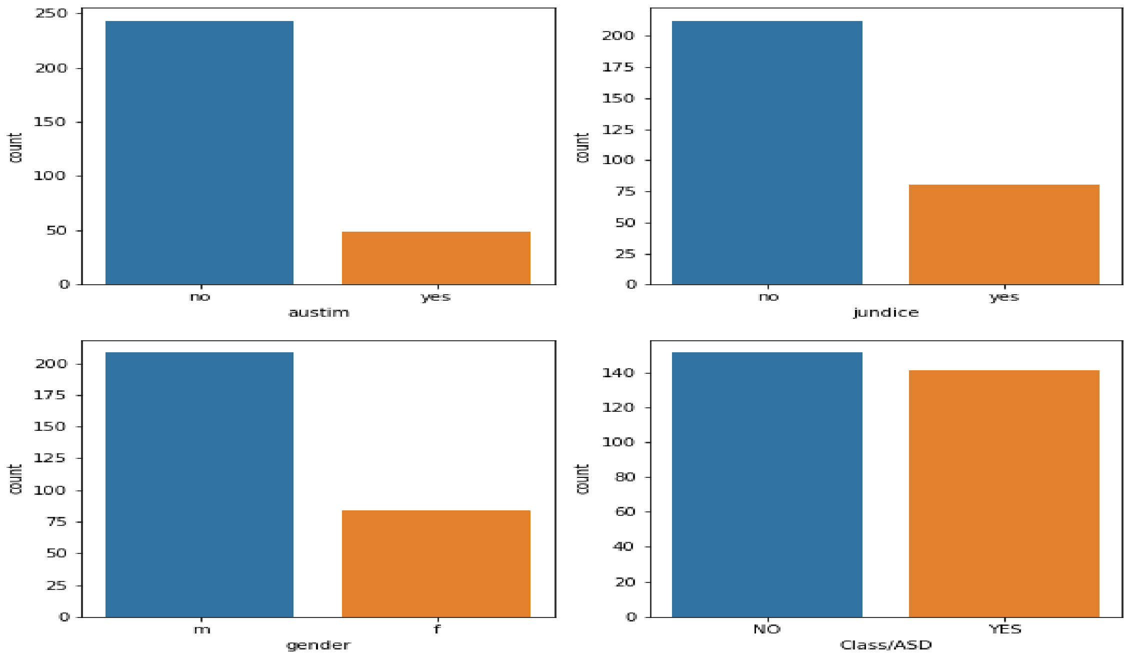

Figure.2: Distribution of variables in Children Dataset

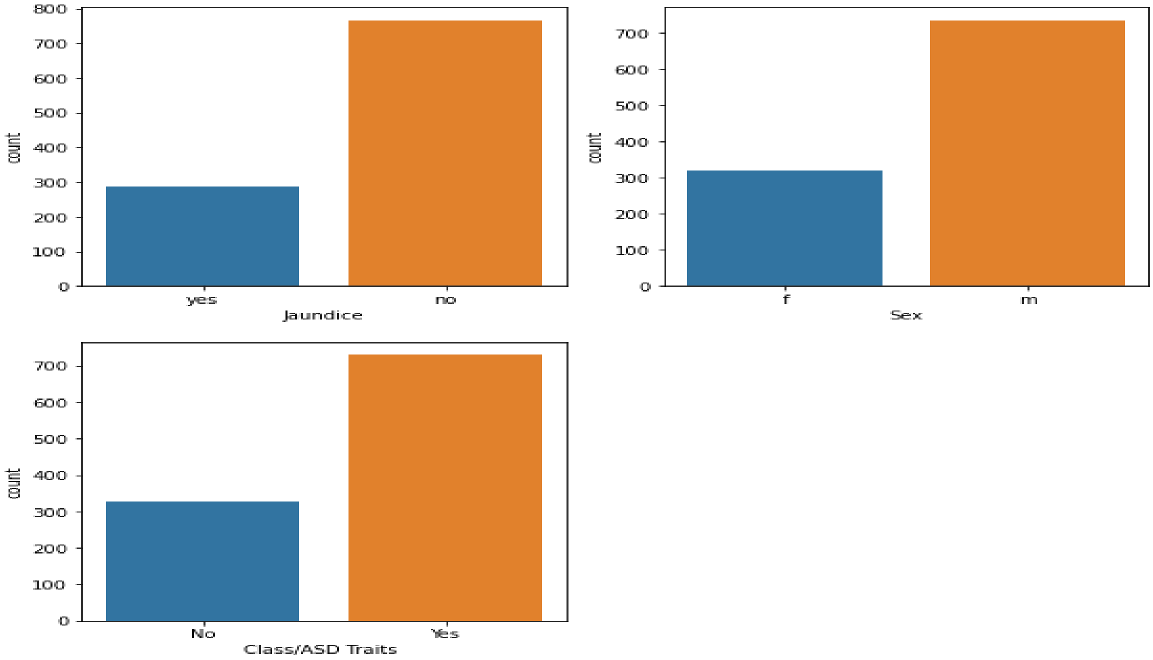

Figure.3: Distribution of variables in Toddler Dataset

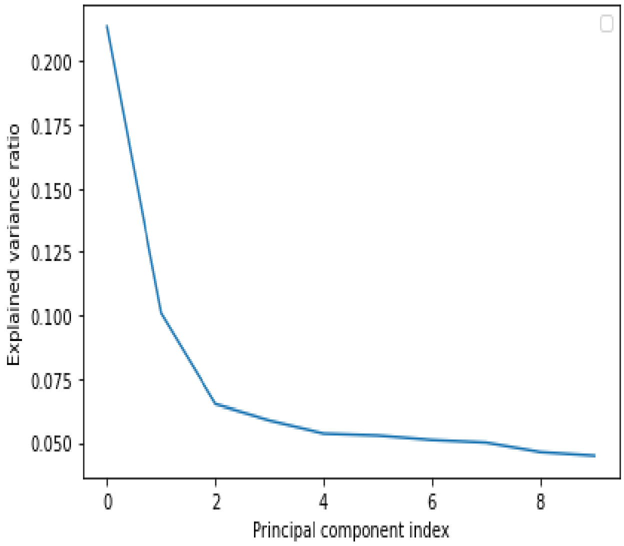

Figure.4: Explained variance ratio of Scaled data

The explained variance ratio is an array of the variance of the data explained by each of the principal components in the data. It can be expressed as a cumulative sum. From the Figure-4, we will have an idea to consider size of principal components. The graph is representation of principal components size and explained variance ratio of transformed data.

4. Building the stacked-ensemble model for ASD Pre-diagnosis

The study focused on a stacking ensemble approach for the predictions of ASD pre-diagnosis especially in children data sets. Missing values and outliers were discovered and imputed with median values prior to learning as a data pretreatment step.

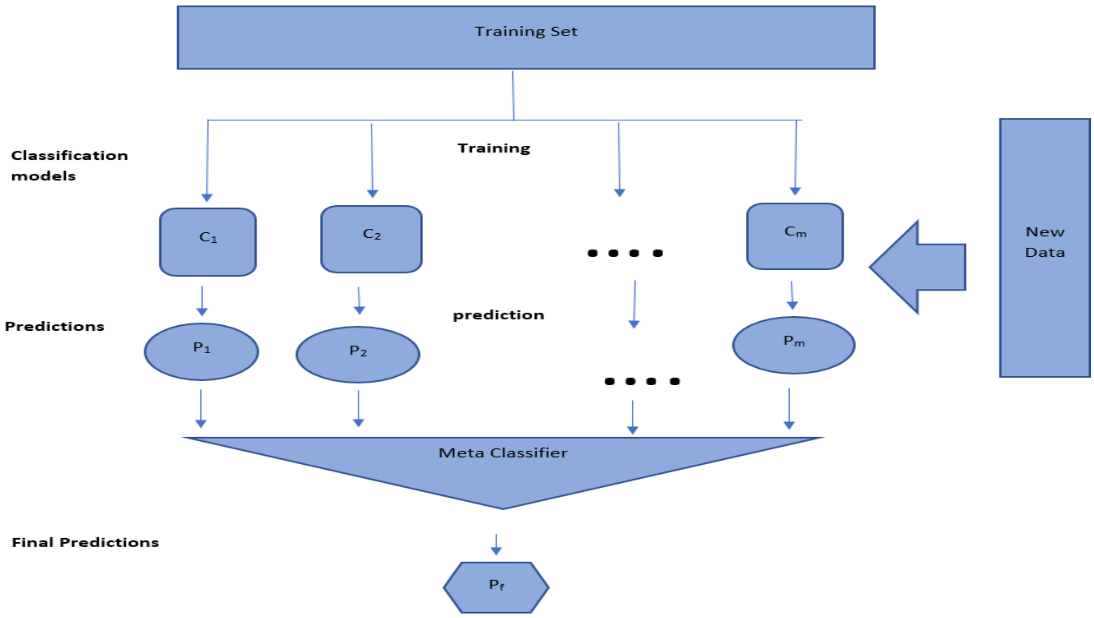

Figure- 5: Representation of Processing of the Stacking Ensemble Algorithm

In stacking mechanism base learner to be selected to build an efficient model. In order to select base learner, several machine learning algorithms like Logistic regression, Decision tree, Random Forest, KNN, Support vector machine, Gaussian naive bayes are utilized which simultaneously maximizes the classification accuracy. Among all them, by stacking Logistic Regression, Decision Tree and Random Forest our model has best accuracy. As for model combination, a meta-classifier that combines the predictions of the base learners is known as stacking approach. The figure-5 shows the process of obtaining the final prediction with the stack-based ensemble model. Stack generalization is a new way of integrating several classifiers such as Logistic regression, Decision tree, Random Forest, KNN, Support vector machine, Gaussian naive bayes. which consists of two stages: at level zero we have basic learners and stacking model learners are at level one; at level zero, multiple separate models are used to learn from the dataset, and the output of each model is utilised to create a new dataset which helps to create an impact in the performance. The comparison findings show that the stacking method for ADS pre-diagnosis (SEC_AP) outperforms a number of different ML approaches. The complete idea of the stacked-ensemble model for ASD Pre-diagnosis is shown in algorithm 1.

Algorithm Ensemble Learning:Stacking

Input:The Original Dataset $Z=\{(x_1,y_1),......,((x_i,y_i);$

Base-level Learner strategy $L_1,....,L_T;$

Meta-level Learner strategy $L;$

Ouptput: $M(x)=h(h_1(x),h_2(x),.....,h_K(x))$

Begin

Base $-$levellearner $h_k$training using $'L_k'$on Dataset Z

for $k=1,2,......,K$

$h_k = L_k(Z)$

end

$\hat{Z}=\varphi;$ //New dataset

Classsification of Taring Set x_j using h_k

for $k=1,2,......,i$

for $k=1,2,......,K$

$c_{jk}=h_k(x_j)$

end

$\hat{Z}=\hat{Z}\cup\{((c_{j1},c_{j2},.........,c_{jK}),y_j\}$

end

Meta $-$levellearner $\hat{h}$ training using $'L'$on Dataset $\hat{Z}$

$\hat{h}=L(\hat{Z})$

end

Figure 6. Algorithm-1 for ensemble learning-stacking

4 Results and Discussion

4.1. Data set

The proposed SEC_AP model was evaluated on a real dataset [12][13] [21-22] i.e.., from the UCI repository and Kaggle related to children in different stages. The data set has 21 variables in Children dataset and 19 variables in toddler’s dataset and collected from the 292 and 1054 samples. These datasets related abbreviations and variables information are listed in Table 1.

Table -1: The Autistic Spectrum data sets used in the study

Dataset	Sample size	Feature size including class label	Classes	Presenceof missing attribute	Presence of noisy attributes
Autistic Spectrum Disorder Screening Data for Children	292	21	ASD/Non-ASD	Yes	Yes
Autism Screening data for toddlers	1054	19	ASD/Non-ASD	Yes	Yes

4.2. Performance measuring:

Any machine learning model, performance evaluated based on the metrics in Table-2. To understand the number of correct predictions and proportion of predictions based on varying threshold values.

Table-2: Description about performance metrics

Performance measure	Description
Confusion Matrix	N*N matrix used to measure performance of classification problem
True Positive	Data point actual and predicted class is 1
True Negative	Data point actual and predicted class is 0
False Positive	Data point actual class defined by 0 and predicted class by 1
False Negative	Data point actual class defined by1 and predicted class by 0
Accuracy	Total number of correct predictions proportion
Precision	Correct Proportion of positive predictions
Recall	Proportion of Actual correct positive predictions
F1-score	It is weighted mean of precision and recall.

The performance metrics that are used for evaluation of the model are Precision, Recall,F1-score, and accuracy.

Accuracy is the ratio of correctly predicted data points made to the total number of data points predictions performed.The accuracy obtained for diagnosing the disorder using SEC_AP model is nearly 100%. The formula used to calculate accuracy is:

$$Accuracy = \frac{No\, of\ Predictions}{Total\, no\, of\ Predictions}$$

Precision is the ratio between correct positive predictions made by the SEC_AP proposed model to the total actual positive predictions. Theprecision obtained is 1.0 which is a perfect precision value gained by the model. The formula used to calculate precision is:

$$Precision = \frac{No\ of\ \ correct\ positive\ predictions}{Total\ No\, of\ \ Positive\, Predictions}$$

Recall is the ratio between correct positive predictions made by the model to total positive examples. The recall valueobtained is also 1.0 which is a high and good value. The formula used to calculate recall is:

$$Recall = \frac{No\ of\ \ correct\ positive\ predictions}{Total\ No\, of\ values\, in\ Positive\, Predictions}$$

F1-score is the weighted average of precision and recall values. The f1-score obtained is 1.0.
The formula used to calculate f1-score is:

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

4.3. Results

Table-3: Comparison of approaches in terms of accuracy, precision, recall, F1-score

	ASD Children Data				ASD Toddler Data			
	Accuracy(%)	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82.91	0.77	0.81	0.78	79.84	0.78	0.67	0.72
K-Nearest Neighbor (k=1)	86.22	0.72	0.76	0.73	83.47	0.75	0.71	0.72
Gaussian Naïve Bayes	72.61	0.67	0.83	0.74	79.23	0.67	0.81	0.73
K-Nearest Neighbor(k=10)	88.91	0.85	0.89	0.86	81.47	0.81	0.76	0.78
Decision Tree	67.52	0.55	0.64	0.59	78.12	0.80	0.67	0.72

Support Vector Machine	62.00	0.59	0.47	0.52	74.2	0.72	0.81	0.76
Random Forest	74.91	0.77	0.63	0.69	86.41	0.87	0.73	0.79

We can observe the results of each single classifier before applying PCA.We explored two different datasets using single machine learning classifiers and analyzed the outcomes are shown in table-3. By comparing results of different single learning classifiers, we had an inference that developing a new model will help in prediction of autism at early stages. To improvethe accuracy and reduce execution time proposed an approach of applying PCA and Stack Ensemble Classification for Autism pre-diagnosis (SEC_AP).

Table-4: Comparison of approaches based on SEC_AP model in terms of accuracy, precision, recall, F1-score

ASD Children Data					ASD Toddler Data			
	Accuracy(%)	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score
Logistic Regression	94.91	0.81	0.95	0.87	91.84	0.97	0.94	0.95
K-Nearest Neighbor (k=1)	93.22	0.72	0.97	0.82	90.47	0.63	0.87	0.73
Gaussian Naïve Bayes	96.61	1.00	1.00	1.00	89.23	1.00	0.88	0.93
K-Nearest Neighbor(k=10)	94.91	1.00	0.93	0.96	90.47	0.84	0.86	0.84
Decision Tree	91.52	0.85	0.81	0.82	96.12	1.00	1.00	1.00
Support Vector Machine	96.00	1.00	1.00	1.00	92.2	0.72	0.81	0.76
Random Forest	94.91	0.87	0.63	0.73	91.41	1.00	0.93	0.96
Proposed Model(Random Forest+Gaussian Naïve Bayes)	100	1.00	1.00	1.00	100	1.00	1.00	1.00

Comparison of approaches in-terms of accuracy, precision, recall and F1-score based on the proposed model (SEC_AP) is shown in table-4. Accuracy is important performance metrics to evaluate the model based on entire data points. Currently, there is no rapid and reliable diagnostic measuring test that can identify ASD at early days. We created an automated ASD prediction model using the minimal behavior sets from each diagnostic dataset. Significant results are shown by using SEC_AP model rather than the previous study models.

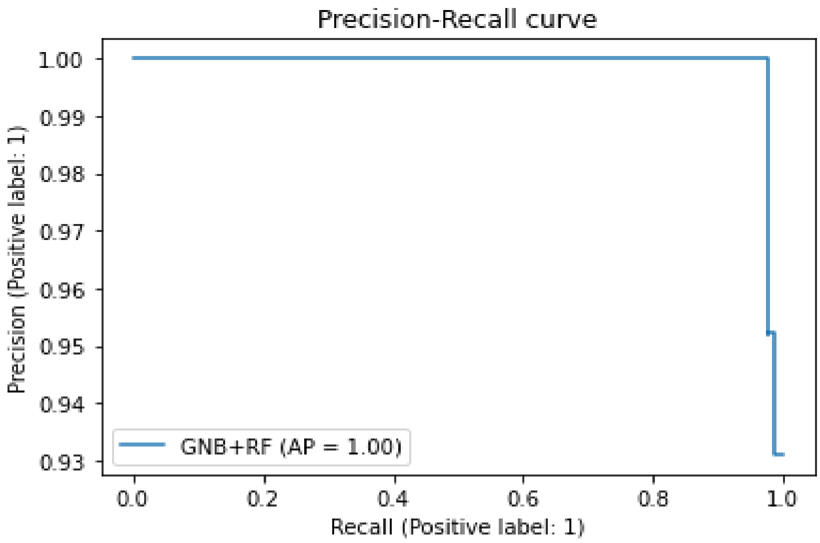

Figure-7: Representation of Precision-Recall curve using GNB+RF model on Children Dataset.

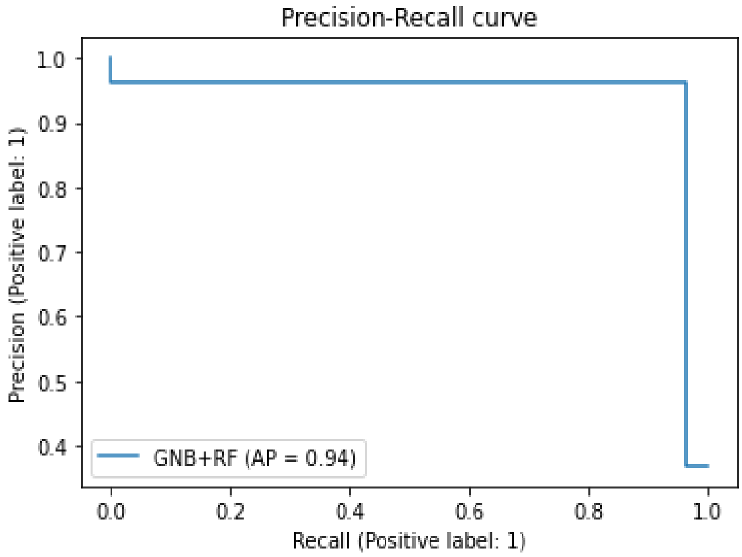

Figure-8: Representation of Precision-Recall curve using GNB+RF model on Toddler Dataset.

To show the tradeoff between precision and recall at different thresholds, Precision-recall curves are highly recommended. A higher area under the curve indicates high precision, which corresponds to a low false rate, and a high recall rate, which corresponds to a low false negative rate. The PR-curve of proposed model for children dataset shown in figure-7 with AOC=1.00 and for toddler dataset the PR curve is shown in figure-8 with AOC=0.94. Precision and recall are analyzed as the best metrics for evaluation of proposed model for diagnosing autism.

4.4. Strengths of the study Using these findings

This section discusses about the limitations of previous study related to the machine learning models which were used for ASD diagnosis, includes the objective of bringing attention to important issues such as data pre-processing, data privacy and data quality while getting desired results. The following are the major strengths in our research study

- Combining the greatest machine learning classification algorithms using the concept of stacking and proposed a model for diagnosing ASD.
- For better understanding of ASD, high level of classification reliability to be achieved.
- Performance metrics have improved for ensemble-based stack model When compared to single-core models.
- A comparison of the proposed model (SEC_AP) results in terms of accuracy, precision, recall andF1-Score.
- Precision-Recall curves for the proposed model represents high area under the curve which showsthe better performance of classification proposed model.

5. Conclusion and future work:

ASD can be observed in early stages of life which affect the individual's overall cognitive, emotional, social, and physical health. In this study, we proposed an ASD diagnosis model for children and toddler datasets using Stack ensemble learning approach and which complements to the conventional single learning methods. This research study done in three stages. At first stage, applied feature selection method i.e., Principal Component Analysis (PCA) to retrieve optimal features of children data set. Later, in second stage, ASD is diagnosis with predictive model is designed using various base classification techniques which includes Random Forest Classifier (RFC) and Naïve Bayes (NB) to children dataset. At the last stage, to improve the performance of ASD prediction model, applied stack ensemble learning method with mentioned base learners. The results shows that proposed ensemble based predictive model is best for ASD diagnosis for the children and toddler datasets at early stages with the accuracyof 100% than the base Machine Learning methods. The proposed model (SEC_AP) has better performance in terms of accuracy, precision, Recall and F1-Score.Future work for the proposed model can be enhanced using the hyper parameter tuning approaches. And the research study can be extended with large data related to Children autism to identify various ASD traits at different stages.

References:

[1] . He, L., Li, H., Holland, S. K., Yuan, W., Altaye, M., and Parikh, N. A. (2018). Early prediction of cognitive deficits in very preterm infants using functional connectome data in an artificial neural network framework. *Neuroimage Clin.* 18, 290–297. doi: 10.1016/j.nicl.2018.01.032

[2] Heinsfeld, A. S., Franco, A. R., Craddock, R. C., Buchweitz, A., and Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. *Neuroimage Clin.* 17, 16–23. doi: 10.1016/j.nicl.2017.08.017

[3] Cromer J. U.S. Army. 2018 Apr 05. Autism: fastest-growing developmental disability URL: https://www.army.mil/article/203386/autism_fastest_growing_developmental_disability [accessed 2019-04-17]

[4] Baio J, Wiggins J, Christensen DL, Maenner MJ, Daniels J, Warren Z, et al. Prevalence of Autism Spectrum Disorder Among Children Aged 8 Years - Autism and Developmental Disabilities Monitoring Network, 11 Sites, United States, 2014. MMWR Surveill Summ 2018 Dec 27;67(6):1-23

[5] Lord C, Rutter M, Goode S, Heemsbergen J, Jordan H, Mawhood L, et al. Autism diagnostic observation schedule: a standardized observation of communicative and social behavior. J Autism Dev Disord 1989 Jun;19(2):185-212.

[6] H. Xiao, Z. Xiao, and Y. Wang, ''Ensemble classification based on supervised clustering for credit scoring,'' Appl. Soft Comput., vol. 43, pp. 73–86,
Jun. 2016.

[7] P. Kordík, J. Černý, and T. Frýda, ''Discovering predictive ensembles for transfer learning and meta-learning,'' Mach. Learn., vol. 107, no. 1, pp. 177–207, Jan. 2018.

[8] A. A. Feitosa Neto and A. M. P. Canuto, ''An exploratory study of mono and multi-objective metaheuristics to ensemble of classifiers,'' Int. J. Speech Technol., vol. 48, no. 2, pp. 416–431, Feb. 2018.

[9] C. Soares, P. B. Brazdil, and P. Kuba, ''A meta-learning method to select the kernel width in support vector regression,'' Mach. Learn., vol. 54, no. 3, pp. 195–209, Mar. 2004.

[10] Silva, Robercy & Canuto, Anne & Barreto, Cephas & Xavier-Júnior, João. (2021). Automatic Recommendation Method for Classifier Ensemble Structure Using Meta-Learning. IEEE Access. PP. 10.1109/ACCESS.2021.3099689.

[11]. N. Qiu, M. Zhai, C. Tang, J. Weng, M. Feng, X. Xiao, T. Xiao, C. Li,Y. Wang, P. Jin, Y. Wang, Y. Da, W. Zheng, and X. Ke, "A study of the makers of early social behaviors of toddlers with high-risk autism spectrum disorder," Chinese Journal of Psychiatry, vol. 52, no. 1, pp.50–56, 2019

[12]R. E. Nickel and L. Huang-Storms, "Early identification of young children with autism spectrum disorder," The Indian Journal of Pediatrics, vol. 84, no. 1, pp. 53–60, 2017.

[13] Ke, Fengkai & Choi, Seung & Kang, Young & Cheon, Keun-Ah & Lee, Sang. (2020). Exploring the Structural and Strategic Bases of Autism Spectrum Disorders With Deep Learning. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.3016734.

[14]Guruvammal, S & Chellatamilan, T & Deborah, L. (2020). Optimal Feature Selection and Hybrid Classification for Autism Detection in Young Children. The Computer Journal. 64. 10.1093/comjnl/bxaa156.

[15]A. S. Heinsfeld, A. R. Franco, R. C. Craddock, A. Buchweitz, and F. Meneguzzi, ''Identification of autism spectrum disorder using deep learning and the ABIDE dataset,'' NeuroImage, Clin., vol. 17, pp. 16–23, Jan. 2018.

[16] T. N. Sainath, A.-R. Mohamed, B. Kingsbury, and B. Ramabhadran, ''Deep convolutional neural networks for LVCSR,'' in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., May 2013, pp. 8614–8618.

[17] Zhang-James, Yanli & Buitelaar, Jan & Group, The & Van Rooij, Daan & Faraone, Stephen. (2021). Ensemble classification of autism spectrum disorder using structural magnetic resonance imaging features. JCPP Advances. 1. 10.1002/jcv2.12042.

[18] Brain, D., & Webb, G. I. (1999). On the effect of dataset size on bias and variance in classification learning. In *Paper presented at the Proceedings of the Fourth Australian Knowledge Acquisition Workshop (AKAW '99), Sydney*.

[19]Davis, J., & Goadrich, M. (2006). The relationship between Precision-Recall and ROC curves. In *Paper presented at the Proceedings of the 23rd International Conference on Machine Learning, Pittsburgh, Pennsylvania, USA*. https://doi.org/10.1145/1143844.1143874

[20]Dichter, G. S. (2012). Functional magnetic resonance imaging of autism spectrum disorders. *Dialogues in Clinical Neuroscience*, **14**(3), 319– 351.

[21]Eslami, T., Almuqhim, F., Raiker, J. S., & Saeed, F. (2021). Machine learning methods for diagnosing autism spectrum disorder and attention- deficit/hyperactivity disorder using functional and structural MRI: A survey. *Frontiers in Neuroinformatics*, **14**(62).

[22]Küpper C, Stroth S, Wolff N, Hauck F, Kliewer N, Schad-Hansjosten T, Roepke S (2020) Identifying predictive features of autism spectrum disorders in a clinical sample of adolescents and adults using machine learning. Sci Rep 10(1):1–11