N. Ajaypradeep, Dr.R. Sasikala. (2021). Child Behavioral Analysis: Machine Learning based Investigation for Autism Screening and early Diagnosis. *International Journal of Early Childhood Special Education (INT-JECSE),* 13(2): 1199-1208. DOI: 10.9756/INT-JECSE/V13I2.211167

Received: 28.06.2021 Accepted: 02.10.2021

N. Ajaypradeep[1]
Dr.R. Sasikala[2]

Child Behavioral Analysis: Machine Learning based Investigation for Autism Screening and Early Diagnosis

Abstract

Autism is a developmental disorder which affects cognition, social and behavioural functionalities of a person. When a person is affected by autism spectrum disorder, he/she will exhibit peculiar behaviours and those symptoms initiate from that patient's childhood. Early diagnosis of autism is an important and challenging task. Behavioural analysis a well known therapeutic practice can be adopted for earlier diagnosis of autism. Machine learning is a computational methodology, which can be applied to a wide range of applications in-order to obtain efficient outputs. At present machine learning is especially applied in medical applications such as disease prediction. In our study we evaluated various machine learning algorithms [(Naive bayes (NB), Support Vector Machines (SVM) and k-Nearest Neighbours (KNN)] with "k-fold" based cross validation for 3 datasets retrieved from the UCI repository. Additionally we validated the effective accuracy of the estimated results using a clustered cross validation strategy. The process of employing the clustered cross validation scrutinises the parameters which contributes more importance in the dataset. The strategy induces hyper parameter tuning which yields trusted results as it involves double validation. On application of the clustered cross validation for a SVM based model, we obtained an accuracy of 99.6% accuracy for autism child dataset.

Keywords: Autism, Behavioural Analysis Machine Learning, Early Diagnosis, Children.

Introduction

Autism Spectrum Disorder (ASD) is a complex neural behavioural disorder which shows symptoms arising from the childhood of an individual. Though there is no perfect cure, an autism affected person can be trained to do his/her daily routines, without the help of others if they have mild or medium levels of autism. The existence of autism neural disorder among young generation has increased rapidly compared to the previous years. In the current modern era diagnosing of ailments in human has become easier, but diagnosing a disorder like autism is a challenging task.

Diagnosis of autism in an individual can be performed only by undergoing a behavioural examination. Many countries across the globe follow DSM-5 (Diagnostic and Statistical Manual) for diagnosis of autism. (American Psychiatric Association, 2019) devised the screening tool DSM-5. There are various other methods too which clinicians use for the screening process of autism. The other

ASD is a behavioural disorder and it is hard to diagnose before the age of 3 years (Reiersen et al., 2017). From the study of (Reiersen et al., 2017), it is found to be that early diagnosis of autism is a challenging task. Practically when a child attains the age of 3 and more, the child will exhibit various behavioural activities such as speech and actions like walking. In many cases, when a child exhibits peculiar symptoms or activities after 3 years, parents tend to undergo a proper treatment. Unlike other disorders, autism cannot be cured with traditional treatments like consumption of drugs or routine medications.

N. Ajaypradeep[1], Research Scholar, School of Computer Science and Engineering, Vellore Institute of Technology, India. Email: n.ajaypradeep2018@vitstudent.ac.in
Dr.R. Sasikala[2], Associate Professor, School of Computer Science and Engineering, Vellore Institute of Technology, India. Email: sasikala.ra@vit.ac.in

tools include Autism Diagnostic Observation Schedule (ADOS) devised by (Lord et al., 2000) and Autism Diagnostic Interview (ADI –R) compiled by (Lord et al., 1994). (Wiggins et al., 2015) made a study on early development in children and this study incorporated methods of ADOS and ADI-R. Depending on the countries and level of affected (mild, moderate and severe) the practices for screening may change.

When a person is affected by autism, he or she may possess one or more of the following symptoms (Centers for disease control and prevention, 2019).

- Not having direct eye contact with others.
- Getting agitated and behaving violently often.
- Possessing less attention towards fellow children and family members.
- Having routine behaviours (playing with a particular toy or creating a kind of unique noise – to distract others attention etc)
- Not possessing speech.

When a child is found with one or more of the above symptoms, the parents or caretakers of the child are advised to undergo proper screening and treatments respectively. Though there is no specific cause for autism various social and geographical factors are considered to be causes (Centers for disease control and prevention, 2020).

- When a child having elder sibling diagnosed with autism, he/she is prone to be affected (Ozonoff et al., 2011).
- When a women is in the stage of pregnancy, when she consume drugs constituting of valproic acid, the child is in risk of autism (Christensen et al., 2013; Strömland et al., 1994).

Early intervention of ASD in children should be performed, so that necessary assistance and care for the autism affected children can be provided (hyman et al., 2020). (Lord et al., 2006) made a work on autism diagnosis from age 2 to 9. This work insisted the mandatory measure of early diagnosis and its impact on the lives of autism affected children. Once early diagnosis is available it will help a huge number of autism affected or partially affected children to improvise themselves by undergoing behavioural therapies.

This paper is structured as (i) Introduction (ii) Literature survey (iii) Participants and methods (iv) Machine learning approach (v) Analysis and Results (vi) Discussion (vii) Limitations (viii) Conclusion and (ix) Future work.

Literature Survey

(Raj et al., 2020) investigated detection of autism spectrum disorder using machine learning techniques. In the study the authors used freely available datasets from the UCI repository. The authors considered three datasets. The three datasets included data gathered from children, adolescents and adults respectively. For analysis the authors used various machine learning algorithms such as KNN, Logistic regression, Support vector machines and Naïve bayes algorithms. Further the authors evaluated the same dataset for deep learning based algorithm called Convolution Neural Networks (CNN). The authors claimed that the accuracy achieved by CNN algorithm was high and efficient when compared with other machine learning algorithms which were used in the study. CNN achieved highest accuracy of 98.30 % for the children dataset, 99.53 % for the adult dataset and 96.88 % for the adolescent dataset. (Parik et al., 2019) made a work on improvising machine learning models in diagnosing autism. In the work the authors employed cross validation technique to enhance the results. This work contributed the base of employing cross validation based strategies to improvise results on machine learning based methods.

(Ajaypradeep & Sasikala, 2021) made a brief review on how machine learning methods are applied for diagnosis of autism and how technological support can be employed as part of identifying autism among children.

(Vaishali et al., 2018) made a study on autism diagnosis using machine learning and neural networks based algorithms. The authors used a dataset retrieved from the UCI repository. The dataset consisted of 21 features. The authors handled the analysis using dimensionality reduction method and they suggested only 10 features is enough for differentiating the autism affected and non autism patients. They attained an accuracy of 97.95 % by employing support vector machines algorithm and 97.60% by applying multi layer perceptron algorithm.

(Pijl et al., 2018) proposed a work on early diagnosis of autism. The work involved 3 major steps which include giving proper coaching to the care takers, implementing various diagnosis tools and creating a team for examining diagnosis. This work also involved the examination of behavioural analysis by evaluating the Intelligence Quotient (IQ) scores of children. For the examination this study also involved traditional methods such as mullen scales of early learning (Mullen, 1995) and the snijders-oomen non-verbal intelligence test (Snijders et al.,1998). In addition with the traditional methods age based examination was also discussed in the study.

(Fletcher et al., 2016) made a study on evaluation of social and expressive skills among children with autism. The work adopted statistical analysis based result evaluation in which traditional autism screening methods like mullen scales of early learning (Mullen, 1995) and Autism Diagnostic Observation Schedule (ADOS) were use for evaluation. This work insisted the usage of technology for finding the skill set of children by engaging them to use an iPad. Various activities of children including game play and object movement identification were recorded and analysed. This work contributed a method to involve real-time evaluation of autism affected children.

(Thabthah, 2017) devised a mobile app for autism diagnosis, which was claimed to be a primary screening tool for autism. This tool was found to be a user friendly and easily accessible tool by all sorts of people belonging to various economic tiers in the society. The tool was claimed as it can be used as an examining method by parents itself as they can measure their child's level of response every time when they use the app.

(Kosmicki et al., 2015) made a study on the factors influencing the impact of machine learning algorithms in the diagnosis of autism using ADOS tool. The authors suggested reduction of Autism Diagnostic Observation Schedule (ADOS) based questions to 8 features and indicated that the same will improve performance.

(Bone et al., 2014) narrated that evaluation with very high effort should be made before applying machine learning methods as it involves medical application. The consequence described in (Bone et al.,2014) work is very important when it comes into any healthcare application based research and not only autism. As it describes an outcome about a patient whether he/she is affected by a disease or disorder, the result which is generated as an end product must be genuine and should not reside on a false output. While coming to autism centric research using machine learning the predicted output shows whether a patient is affected/not affected by autism. (Wall et al., 2012) suggested the effectiveness of using a machine learning based model for autism diagnosis. The study further stated that using machine learning models will increase efficiency of the autism finding rate.

Table 1.

Datasets involved in the study

S. No	Dataset details	Instances	Features
1)	Autistic spectrum disorder screening data for toddlers	1054	21
2)	Autistic spectrum disorder screening data for adult	704	21
3)	Autistic spectrum disorder screening data for adolescent	104	21

Participants and Methods

In our study we employed three datasets obtained from UCI repository (Dua & Graff, 2019). Table 1 represents the datasets. The first data set consist of autism spectrum disorder dataset for toddlers compiled by (Thabtah, 2017) with 1054 instances. The Second data set consist of autism spectrum disorder dataset for adolescent compiled by (Thabtah, 2017) with 104 instances. The Third data set consist of autism spectrum disorder dataset for adult compiled by (Thabtah, 2017) with 704 instances. We trained our model with a group of supervised machine learning algorithms and evaluated the accuracy obtained by each method.

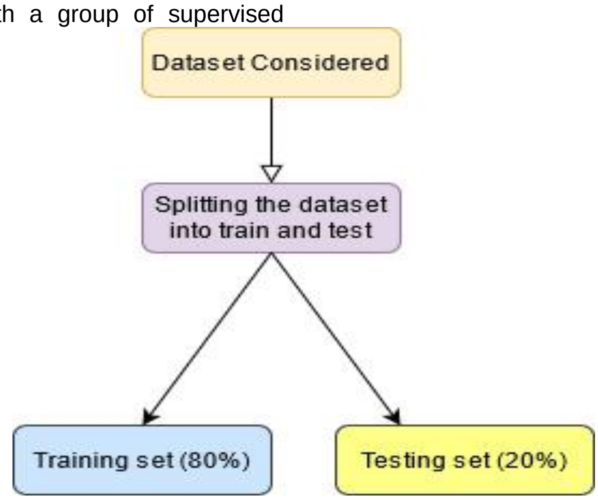
The toddler dataset consist of 21 features with 1054 instances. The features include case no, A1-A10 questions, age in months, “Q chart” score obtained by the child, gender, ethnicity, whether the child was affected by jaundice, whether family member was affected by autism and finally autism trait.

The second dataset is the autism adult dataset which 704 instances were present and the 21 features which include same features as in the toddler dataset. Additionally it included features such as “whether the app was used”, which investigates whether the application for autism screening developed by (Thabthah, 2017) was used or not. The third dataset is the autism adolescent dataset which consist of 104 instances.

From the datasets it is found that 21 features were found to be common among all the three datasets. From the 21, very vital attributes are considered for evaluation using ML algorithms. Various traditional supervised machine learning algorithms are employed and evaluated on the above datasets. The supervised machine learning algorithms including support vector machines, KNN and Naïve bayes algorithms were used for analysis and evaluation. For each of the above dataset the computed values were cross validated for its accurateness and efficiency. For the purpose of cross validation we employed strategies like k-fold cross validation and clustered cross validation using which a perfect model interpreting high accuracy can be devised.

The Machine Learning Approach

There are various validation and evaluation strategies available when it comes into machine learning. In our work we present how efficient the clustered cross validation works, when compared to traditional cross validation methods. We separate our work into three parts. The first part describes validating the considered datasets using traditional method of train, test and split in which the dataset is evaluated with 80 % for training and 20 % for testing. The second part describes k-fold cross validation and the final part describes the usage of clustered cross validation. Figure 1 describes the train-test-split strategy.



DOI: 10.9756/INT-JECSE/V13I2.211167

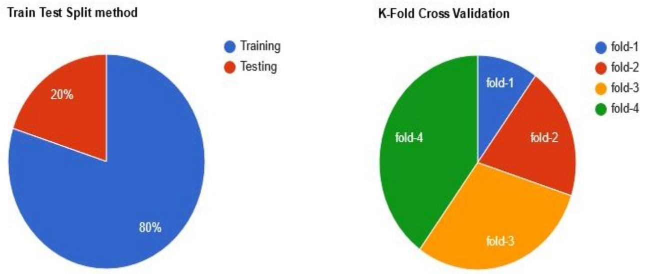


Figure 1.

Traditional Train Test Split Method of Validation

The traditional method of train test split in the most commonly used validation technique. This method validates the model “one time” and there is no provision for repeated validation. This method is practically easier in implementation and consumes very less time but it has disadvantages too. This method may lead the model to over fitting and may also end up in lesser accuracy rate when the dataset is relatively small. The second method of K-fold cross validation overcomes some of the flaws of the train test split. In K-fold method we split out data into “k” subsets. For instance, if there are 50 numbers of data entries in a dataset, we can employ “5 folds” in which first 10 data instances will considered for testing and other 40 instances will be used for testing in first fold. Similarly in 2nd fold the second set (11-20 data instances) will be used for testing and other parts will be used for training. The table illustrates the working idea of k-fold cross validation. For better understanding the table represents how 15 data entries are been split into test and train parts, in which we split Likewise, based on number of data instances we may define the number of folds, which may result in enhanced accuracy and efficiency of the model.

The k-fold cross validation method overcomes drawbacks generated by the train-test-split method. The k-fold validation method considerably reduces the risk of over fitting. Though it has certain advantages over train-test-split method it also generates certain flaws while handling the data. The k-fold cross validation takes more computational time when compared to the train-test-split method as it involves more computations to be done. Figure 2 represents the K-Fold cross validation strategy.

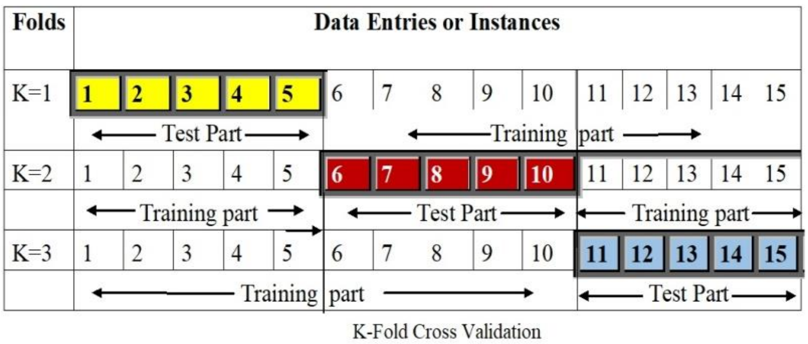


Figure 2.

K-Fold Cross Validation Strategy

The final methodology in which we evaluate the dataset is the Clustered Cross Validation (CCV) method. The clustered cross validation method is an extension of the above discussed validation strategies. Clustered cross validation method addresses the issues of other two validation methods. This method can be employed to achieve maximum accuracy. The CCV method consists of two layers, one is the inner layer and another is the outer layer.

The outer layer consists of training set sliced into various folds. This loop is used for the estimation of performance. In other words, the entire dataset is split into various fragments and the number of fragments depends on the instances in the dataset. For understanding in the figure 3, we consider a dataset of 100 instances. We split the total dataset into 5 slices with 20 instances in each. The outer loop works as same as that of the “k-fold” cross validation. Another part called inner loop constitutes the task of hyper parameter tuning. The parameters which comprise efficient results in the outer loop is considered. The selected parameters are again validated against outer loop.

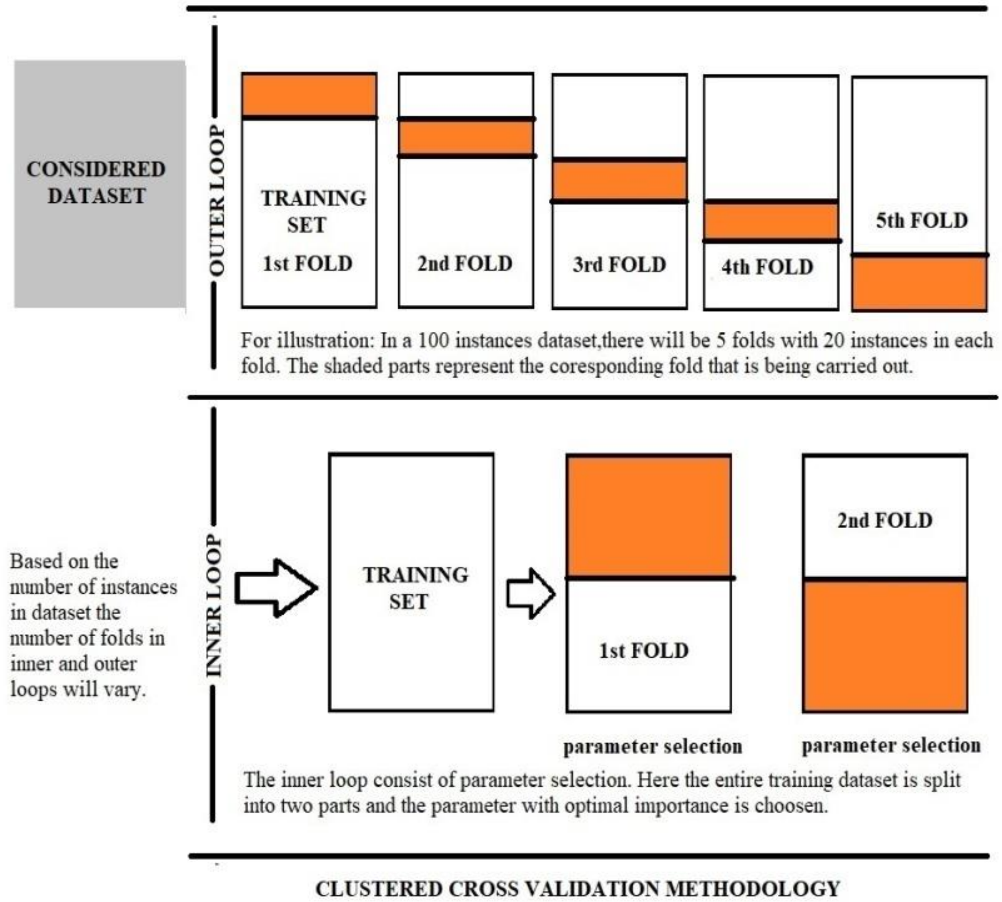


Figure 3.

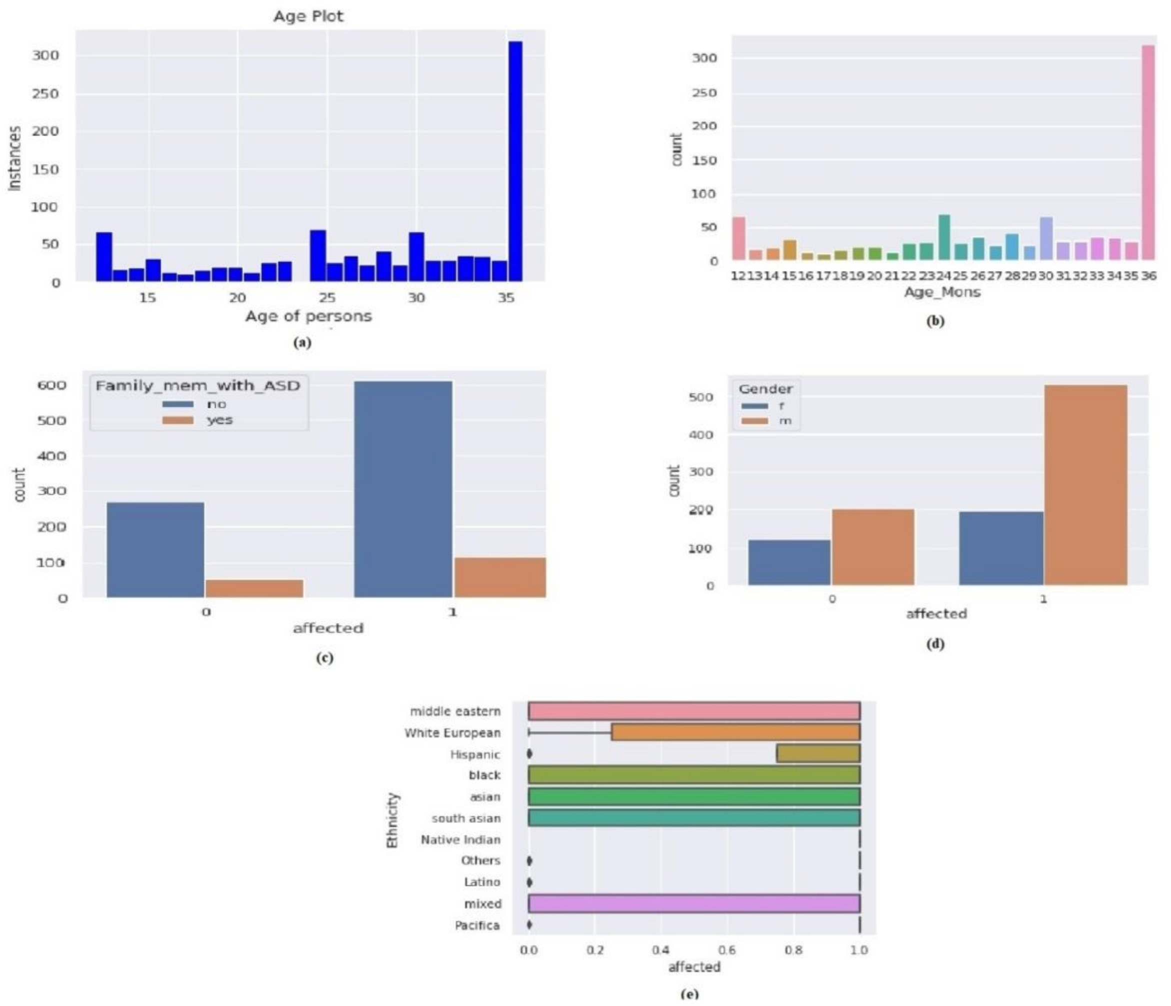
Strategy of Clustered Cross Validation

As part of hyper parameter tuning, for our datasets we employed very high importance contributing features such as age, whether the patient had diseases like jaundice, score of questionnaire used in the screening and ethnicity of the patient. Since the strategy involves two loops in validation this approach is said to be as clustered cross validation. The approach includes running a small unit of training subset on the model. Additionally it is evaluated on the validation subset.

Finally the chosen parameters and the integrated training set (including training subset and the validation set) are made to run on the test set. The evaluated results narrate the clustered cross validated accuracy of the dataset considered. CCV can be used when the dataset is small and have observation count in thousands. In our work we considered 3 datasets and they have 1054,704 and 104 observations in each respectively. Since we have less data in the observations we employ clustered cross validation for verifying the correctness of the accuracy scores predicted by the machine learning algorithms.

As our datasets comprise of less number of instances, it is possible to apply the method of clustered cross validation. When the dataset is relatively large it is not possible to apply a machine learning based method. But the same can be addressed by applying a deep learning based model. Hyper parameter tuning is possible in deep learning methods too by reducing the number of instances which is call as dimensionality reduction.

Figure 4 represents various plots describing the visualisation of the dataset considered. The plot (a) describes the age of children in months as scale (15-20-25 months) who are affected. The plot (b) describes the same age of affected but the scale ranges from (12-36 months). This plot indeed explains in briefer about the age parameter in the dataset. The plot (c) describes family member history affected with autism. The plot (d) describes male vs. female ratio. The plot (e) shows the respective country or region of the person affected. We deploy “sea born” based method for data visualisation. Sea born devised by (Michael Waskom et al., 2017) is a library function in python used for the visualisation of the data parameters. Sea born libraries are known for enhanced representation of data. When dataset is more complex, the user needs to afford more effort to understand and manipulate the data. In order to reduce the ease of the user, these visualisation based tools can be deployed. There are many data visualisation tools in python. One among them is the sea born toolkit.



SNS plot graphs of the autism child dataset

(a)Age of affected persons plot ; (b) Age in months plot; (c)History of family members affected/not affected by autism plot ;

(d) Male vs Female plot ; (e) Ethnicity of the affected plot

Figure 4.

SNS Plot of Dataset Parameters

Analysis and Results

Results Representing Train-test-split and k-fold Cross Validation

Supervised machine learning algorithms known for predicting high accuracy results are applied in the considered datasets. The objective of our work is to compare the results generated by the algorithms on the datasets and validating the results by a well structured clustered cross validation method. By adopting CCV as discussed in the machine learning approach section, the effective verification of the predicted results can be determined.

Machine learning algorithms such as support vector machines, Naïve bayes, and k-nearest neighbours were considered for evaluation of the dataset. Initially the model is build with 80 % data for training and 20 % data for testing. The parameters of "Precision", "Recall" and "F1" score are considered for the performance evaluation and the same is described in the figure 5. The accuracy produced by each algorithm after k-fold cross validation is also tabulated in the table 2 for the autism toddler dataset. It is been observed that from the 3 machine learning algorithms applied on the autism toddler dataset yield accuracy scores ranging (93% to 98%), in which SVM achieved the maximum accuracy score of 98%.

Table 2.

Autism Toddler Dataset Result Analyses for K-Fold Cross Validation

Algorithms Parameters	**K-Nearest Neighbour Algorithm**	**Naïve Bayes**	**SVM**
Precision	99	96	100
Recall	97	95	99
F1 Score	98	95	99
Accuracy	97%	93%	98%

In the autism adult dataset maximum accuracy was achieved by SVM algorithm (with 98% accuracy). Based on the three algorithms we obtained result accuracies ranging from (86% to 99%). In the autism adolescent dataset, the maximum accuracy was achieved by KNN algorithm (with 99 % accuracy) and the least was achieved by Naive bayes algorithm. The accuracy scores ranges from (81 % to 99 %) which is described in the table 3. It is observed that on evaluating the three datasets, we found SVM algorithm based on linear kernel achieved maximum accuracies in two datasets and KNN in one dataset. The table 4 represents results of k-fold cross validation on the adolescent dataset.

Table 3.

Autism Adult Dataset Result Analyses for K-Fold Cross Validation

Algorithms	**Naïve Bayes**	**KNN**	**SVM**
Parameters			
Precision	67	100	100
Recall	89	93	96
F1 Score	77	96	98
Accuracy	86%	88 %	96.2%

Table 4.

Autism Adolescent Dataset Result Analyses for K-Fold Cross Validation

Algorithms	**Naïve Bayes**	**K-Nearest Neighbour Algorithm**	**SVM**
Parameters			
Precision	74	98	81
Recall	100	98	100
F1 Score	85	98	89
Accuracy	81%	99%	88%

Results Representing Double Validation Using Clustered Cross Validation

The clustered CV method is employed as part of verifying the SVM algorithm results. In the process a linear SVM algorithm based kernel is employed. As described the clustered cross validation method consist of two loops. In each of the considered dataset we iterated the outer loop with 50 turns and inner loop with 20 iterations. Based on the turns the number of times the loops executes will be increased. This will result in a robust and efficient way of verifying the correctness of the result generated by the SVM algorithm. Since the SVM algorithm with linear kernel generated high accuracy score, we used the same for the process of cross validation.

Initially the cross validation is made on toddler autism dataset. In this the clustered cross validation score achieved was 99.6 %. After the process the second dataset of autism adult was considered and the output accuracy obtained was around 99.4 %. Finally the autism adolescent dataset was clustered cross validated, on which the accuracy score obtained was 99.1 %. Considerably the clustered cross validated scores were higher than that of k-fold cross validated scores as the validation process is stringent and the data is trained well in this accord. The table 5 displays the accuracies before and after clustered cross validation.

Table 5.

S. No	**Dataset**	**SVM Score of K- Fold Cross Validated Model**	**SVM score of Clustered Cross Validated Model**
1)	Autistic spectrum disorder screening data for toddlers	98%	99.6%
2)	Autistic spectrum disorder screening data for adult	96.2%	99.4%
3)	Autistic spectrum disorder screening data for adolescent	88%	99.1%

Result Analyses for Clustered Cross Validation

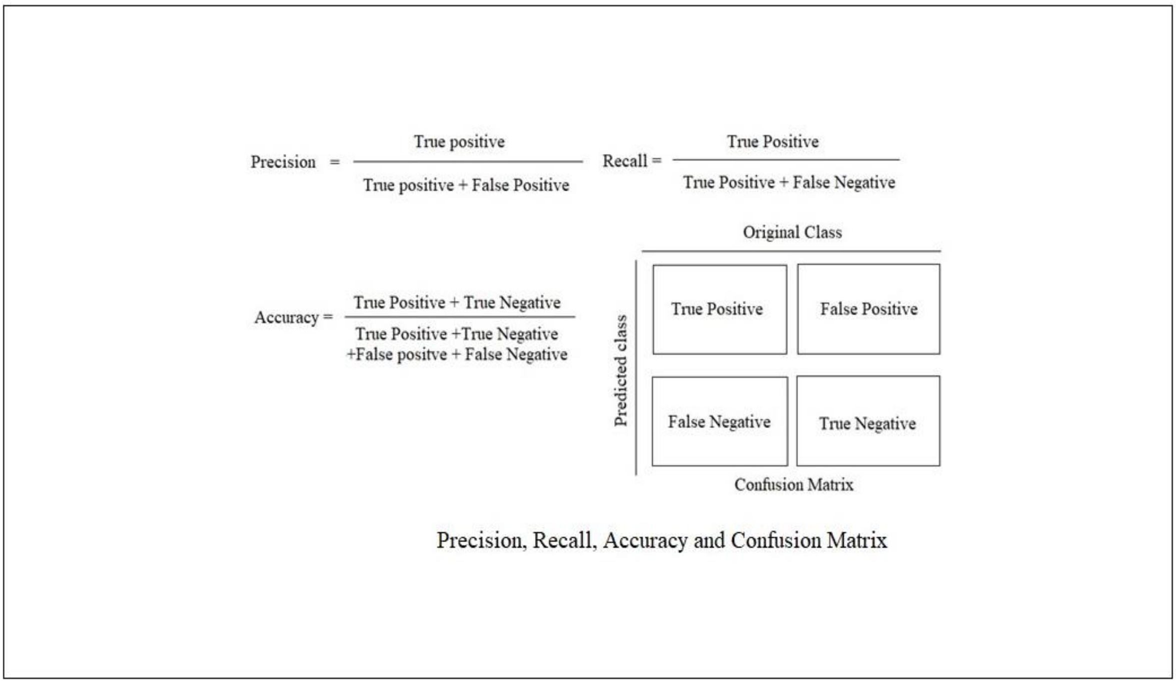


Figure 5.

Evaluation Parameters

Discussion

The objective of autism diagnosis is vital when compared to other applications of machine learning based models. Since it involves direct diagnosis of the disorder, higher importance should be given to the algorithm which makes diagnosis better. In some related works, various authors claimed that autism diagnosis can be made by machine learning algorithms. (Raj et al., 2020) claimed that the deep

learning based algorithm, CNN can be applied to the datasets and highlighted that CNN generated highest output when compared to machine learning algorithms. But in our work we employed machine learning based algorithms to evaluate the same datasets and attained maximum outputs by employing clustered cross validation strategy. Additionally deep learning based algorithms can be applied when the datasets are too large in size, for instance more than 1, 00,000 instances of the data.

But in our case the datasets are of lesser size, hence preferring machine learning based algorithms is more beneficial than employing a deep learning based algorithm which is time consuming too.

In (vaishali et al., 2018) work the authors considered only one dataset and employed dimensionality reduction to perform analysis on the data. The results obtained in our work are better than the results generated by their work; additionally we made investigation on 3 related datasets. Though dimensionality reduction is a good solution when there is more number of features, the features which we neglect should be identified initially and those features should be prioritised based on their impact and importance which they reflect on the considered dataset. Randomly neglecting certain features in a particular dataset may result in false results which may lead to collapse the objective of performing a particular experiment. This is considered to be as an important aspect because the generated output of an experiment predicts whether a person is affected or not affected by autism. The generated output should be accurate in its efficiency. If the estimation fails a health person may be diagnosed with autism or an autistic person may be diagnosed as a healthy person.

(Pijl et al., 2018) work concentrated on all aspects of clinical practice based autism diagnosis. The third step of the study which employs the therapist / trainer for screening is an important aspect. Since the first and second step involves preliminary screening the third step conducted by an expert therapist will decide the existence of autism. The statistical method used in the study can be improvised by a machine leaning based method to lessen the human ease and also for improvising the efficiency.

(Fletcher et al., 2016) work nominated the usage of an iPad based object detection functionality task. Though this work tends to be a technology oriented methodology for performing screening task it involves some risks and barriers too. Parents are supposed to use the iPad and they should know how to use it. In countries with less literacy rate, the same may not be possible. Additionally children using the tab may mishandle the device which may result in permanent failure of device operation too. Thus there are many practical issues in using the iPad based method.

Limitations

In our work we employed clustered cross validation method to double validate the results. This strategy can be applied only when the dataset instances ranges in thousands. In our study, the maximum number of instance is in the autism toddler dataset with 1054 entries and so we applied clustered CV. When the dataset is too large, the application of deep learning algorithms will be a good solution for evaluation. Additionally the results obtained by the discussed algorithms may vary as the dataset instances increase.

Conclusion

In current scenario there is a huge necessity for inter domain based research. Though autism is a psychology based field, various works have claimed the importance of applying machine learning in autism diagnosis. In developing and under developing countries there is no proper awareness regarding diseases like autism. The centres for research and evaluation of disorders like autism are very less. When it comes into treatment for diseases like autism, only the people in higher tiers of the society are affordable. Hence it is not possible for commoner to undergo high-tech treatment and screening. Hence government bodies and non-governmental welfare organisations should afford helping hands for the needy deserving such treatments. In many cases a person would have been affected and parents would identify the existence only in 3 or 4 years. If the diagnosis is performed at an early stage, it will help the affected person to develop himself/herself in a lot of means. For such early screening mobile app developed by (Thabthah, 2017) will be useful hands-on tool for the parents to check the child's growth.

In our work we suggested the usage of clustered validation strategy in order to verify the results generated by support vector machines algorithm. A large scale research involving experts from medicinal and data science can be encouraged, so that more robust and in depth research moralities can be devised in future for the welfare of the society.

Future Work

Our future work will be on applying the same methodology with a real time collected dataset and thereby verifying the efficiency and throughput of the algorithms.

References

Reiersen, A.M. (2017). Early identification of autism spectrum disorder: is diagnosis by age 3 a reasonable goal?. *Journal of the American Academy of Child and Adolescent Psychiatry*, *56*(4), 284-285.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders (DSM-5®)*. American Psychiatric Pub.

Wiggins, L.D., Reynolds, A., Rice, C.E., Moody, E.J., Bernal, P., Blaskey, L., Rosenberg, S.A., Lee, L.C., & Levy, S. E. (2015). Using standardized diagnostic instruments to classify children with autism in the study to explore early development. *Journal of autism and developmental disorders*, *45*(5), 1271–1280. https://doi.org/10.1007/s10803-014-2287-3

Lord, C., Risi, S., Lambrecht, L., Cook, E.H., Leventhal, B.L., DiLavore, P.C., & Rutter, M. (2000). The Autism Diagnostic Observation Schedule—Generic: A standard measure of social and communication deficits associated with the spectrum of autism. *Journal of autism and developmental disorders*, *30*(3), 205-223.

Lord, C., Rutter, M., & Le Couteur, A. (1994). Autism Diagnostic Interview-Revised: a revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders. *Journal of autism and developmental disorders*, *24*(5), 659-685.

Centers for disease control and prevention. (2019). *Autism Spectrum Disorder (ASD).* https://www.cdc.gov/ncbddd/autism/screening.html

Centers for Disease Control and Prevention. (2020). *Autism Spectrum Disorder (ASD)*. https://www.cdc.gov/ncbddd/autism/facts.html

Ozonoff, S., Young, G.S., Carter, A., Messinger, D., Yirmiya, N., Zwaigenbaum, L., & Hutman, T. (2011). Recurrence risk for autism spectrum disorders: a Baby Siblings Research Consortium study. *Pediatrics*, *128*(3), e488-e495.

Christensen, J., Grønborg, T.K., Sørensen, M.J., Schendel, D., Parner, E.T., Pedersen, L.H., & Vestergaard, M. (2013). Prenatal valproate exposure and risk of autism spectrum disorders and childhood autism. *Jama*, *309*(16), 1696-1703.

Strömland, K., Nordin, V., Miller, M., Akerström, B., & Gillberg, C. (1994). Autism in thalidomide embryopathy: a population study. *Developmental Medicine & Child Neurology*, *36*(4), 351-356

Hyman, S.L., Levy, S.E., & Myers, S.M. (2020). Council on Children with Disabilities,Section on Developmental and Behavioral Pediatrics. Identification, evaluation, and management of children with autism spectrum disorder. *Pediatrics*, *145*(1).

Lord, C., Risi, S., DiLavore, P.S., Shulman, C., Thurm, A., & Pickles, A. (2006). Autism from 2 to 9 years of age. *Archives of general psychiatry*, *63*(6), 694-701.

Raj, S., & Masood, S. (2020). Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques. *Procedia Computer Science*, *167*, 994-1004.

Parikh, M.N., Li, H., & He, L. (2019). Enhancing diagnosis of autism with optimized machine learning models and personal characteristic data. *Frontiers in computational neuroscience*, *13*, 9. https://doi.org/10.3389/fncom.2019.00009

Ajaypradeep, N., & Sasikala, R. (2021). Statistical Perspectives and Machine Learning Algorithms: Research Analysis of Technological Support for Autism Diagnosis. *In Education and Technology Support for Children and Young Adults with ASD and Learning Disabilities*, 315-338.

Vaishali, R., & Sasikala, R. (2018). A machine learning based approach to classify Autism with optimum behaviour sets. *International Journal of Engineering & Technology*, *7*(4), 18.

Pijl, M.K., Buitelaar, J.K., De Korte, M.W., Rommelse, N.N., & Oosterling, I.J. (2018). Sustainability of an early detection program for autism spectrum disorder over the course of 8 years. *Autism*, *22*(8), 1018-1024

Mullen, E.M. (1995). *Mullen scales of early learning*. Circle Pines, MN: AGS, 58-64.

Snijders, J.T., Snijders-Oomen, A.W.M., & Tellegen, P.J. (1998). *SON-R 21/2-7: Snijders-Oomen niet-verbale intelligentietest: handleiding en verantwoording*. Swets Test Publishers.

Tellegen, P.J., Laros, J.A., Winkel, M., & Wijnberg-Williams, B.J. (1998). *SON-R 2 1/2-7: Snijders-Oomen* Nonverbal *Intelligence Test; Manual and Research Report*. Swets Test Publishers.

Fletcher-Watson, S., Petrou, A., Scott-Barrett, J., Dicks, P., Graham, C., O'Hare, A., & McConachie, H. (2016). A trial of an iPad™ intervention targeting social communication skills in children with autism. *Autism*, *20*(7), 771-782.

Thabtah, F. (2017). *ASD Tests.* A mobile app for ASD screening.

Kosmicki, J.A., Sochat, V., Duda, M., & Wall, D.P. (2015). Searching for a minimal set of behaviors for autism detection through feature selection-based machine learning. *Translational psychiatry*, *5*(2), e514-e514.

Bone, D., Goodwin, M.S., Black, M.P., Lee, C.C., Audhkhasi, K., & Narayanan, S. (2015). Applying machine learning to facilitate autism diagnostics: pitfalls and promises. *Journal of autism and developmental disorders*, *45*(5), 1121-1136.

Wall, D.P., Kosmicki, J., Deluca, T.F., Harstad, E., & Fusaro, V.A. (2012). Use of machine learning to shorten observation-based screening and diagnosis of autism. *Translational psychiatry*, *2*(4), e100-e100.

Dua, D., & Graff, C. (2019). UCI Machine Learning Repository [http://archive. ics. uci. edu/ml]. Irvine, CA: University of California, School of Information and Computer Science. Failure to detect type 2 diabetes early costing $700 million per year, Diabetes Australia, 8 July 2018. *Google Scholar*.

Fadi, F.T. (2017). Autistic Spectrum Disorder Screening Data for Adult. https://archive.ics.uci.edu/ml/machine-learning-databases/00426

Fadi, F.T. (2017). Autistic Spectrum Disorder Screening Data for Adolescent. https://archive.ics.uci.edu/ml/machine-learning-databases/00420/.

Waskom, M., Botvinnik, O., O'Kane, D., Hobson, P., Lukauskas, S., Gemperline, D.C., & Qalieh, A. (2017). Mwaskom/Seaborn: V0. 8.1 (September 2017). *Zenodo*. http://doi.org/10.5281/zenodo.883859

Heinsfeld, A.S., Franco, A.R., Craddock, R.C., Buchweitz, A., & Meneguzzi, F. (2018). Identification of autism spectrum disorder using deep learning and the ABIDE dataset. *Neuro Image: Clinical*, *17*, 16-23. http://doi.org/10.1016/j.nicl.2017.08.017

Pretis, M. (2009). Early childhood intervention in Austria: An overview of 30 years of development and future challenges. *International Journal of Early Childhood Special Education, 1*(2), 127-137.