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APPLYING MACHINE LEARNING TECHNIQUES TO PREDICT AUTSIM SPECTRUM DISORDER

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Abstract

Nowadays Autism Spectrum Disorder (ASD) is gaining its momentum faster than ever, with the advancement of artificial intelligence, autism can be predicted at quite early stage. This paper aims to propose an effective prediction approach using autism dataset after preprocessing to be suitable with the algorithms to reach the best result. This dataset applied on seven machine learning algorithms: K Nearest Neighbor algorithm, Random Forest algorithm, Decision Tree algorithm, Multilayer Perceptron algorithm, Naive Bayes, AdaBoost, and Gradient Boosting algorithm. The evaluation metrics that will be relied upon in this research and the comparison between the performances of the applied algorithms is: recall, accuracy, precision, and f1-score.

Key words: classification, machine learning, Autism.

INTRODUCTION

ASD, autism spectrum disorder, arises from neurological variations and manifests as a developmental disability. Individuals with ASD commonly experience difficulties in social communication and interaction, alongside exhibiting restricted or repetitive behaviors and interests. Moreover, they may possess distinct learning styles, movement patterns, or attention tendencies. It is worth highlighting that certain individuals lacking ASD may display some of these symptoms. Nevertheless, for those with ASD, these distinct traits can significantly impact their daily lives, presenting formidable challenges (Rutter, 1968)

Signs and Symptoms

Individuals diagnosed with ASD frequently encounter difficulties in social communication and interaction, as well as exhibit restricted or repetitive behaviors and interests. Moreover, people with ASD may possess diverse learning approaches, movement patterns, or attention tendencies. These distinctive traits can significantly impact their daily lives, rendering life particularly challenging. It is worth noting that certain individuals without ASD may also experience some of these symptoms (Baron-Cohen, 2009).

Diagnosis

The process of diagnosing ASD can be challenging as there is no medical test, such as a blood test, available for definitive diagnosis. Instead, doctors rely on observing the child's behavior and development to reach a diagnosis. In some cases, ASD can be identified as early as 18 months of age or even younger. By the age of 2, a diagnosis made by a skilled professional can be considered reliable. However, it is not uncommon for many children to receive a final

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diagnosis later in life, sometimes not until they reach adolescence or adulthood. Unfortunately, this delay in diagnosis means that individuals with ASD may not receive the early assistance they require. (Anderson, 1990)

ASD-related characteristics pertaining to social communication and interaction encompass the following:

- Avoids or lacks eye contact.
- Fails to respond to their name by the age of 9 months.
- Shows limited or no display of facial expressions such as happiness, sadness, anger, or surprise by the age of 9 months.
- Does not engage in simple interactive games like pat-a-cake by the age of 12 months.
- Exhibits minimal or no use of gestures by the age of 12 months, such as waving goodbye.
- Fails to share interests with others by the age of 15 months, for instance, showing someone an object they find appealing.
- Does not point to indicate something interesting by the age of 18 months.
- Does not recognize or show concern when others are hurt or upset by the age of 24 months.
- Does not take notice of other children and join them in play by the age of 36 months.
- Does not engage in pretend play, such as assuming the role of a teacher or superhero, by the age of 48 months.
- In addition to the aforementioned social communication and interaction challenges, individuals with ASD commonly exhibit other related characteristics, which may encompass:
- Delayed development of language skills.
- Delayed acquisition of movement skills.
- Delayed cognitive or learning abilities.
- Manifestation of hyperactive, impulsive, and/or inattentive behaviors (Baron-Cohen, 2009).

Treatment

Contemporary treatments for ASD aim to alleviate symptoms that hinder daily functioning and overall well-being. As ASD manifests uniquely in each individual, people with ASD exhibit distinctive strengths, challenges, and varying treatment requirements. Treatment plans typically involve a multidisciplinary approach, with the involvement of multiple professionals, and are tailored to suit the specific needs of the individual.(Silverman, 2011)

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Risk Factors

Autism spectrum disorder (ASD) does not have a singular cause. Instead, numerous factors, such as environmental, biological, and genetic influences, have been identified as potential contributors to a child's likelihood of developing ASD.(Horvath, 2002)

LITERATURE REVIEW

Autism spectrum disorder is very prevalent and is being worked on increasingly with the advancement of artificial intelligence, in this section, A group of related research will be presented and shown as follows:

(Bhola,2021), A random forest classifier was trained using data from the 2008 Georgia ADDM site, consisting of 1,162 children with 5,396 evaluations. Among them, 601 children met the ADDM ASD criteria based on standard ADDM methods. The classifier utilized words and phrases from these evaluations to predict the case status of ASD. The performance of the classifier was assessed using the 2010 Georgia ADDM surveillance data, which included 1,450 children with 9,811 evaluations. Among them, 754 children met the ADDM ASD criteria. Additionally, ASD prevalence was estimated using predictions generated by the classification algorithm. Overall, the machine learning approach achieved a concordance rate of 86.5% with the clinician-determined case statuses, demonstrating a sensitivity of 84.0% and a positive predictive value of 89.4%.

(Vakadkar, 2021), In order to enhance conventional methods, machine learning techniques have been employed. Our dataset was utilized to develop predictive models using various models such as Support Vector Machines (SVM), Random Forest Classifier (RFC), Naïve Bayes (NB), Logistic Regression (LR), and K-Nearest Neighbors (KNN). The primary goal of our research is to identify early susceptibility to ASD in children, aiming to streamline the diagnosis process. After analyzing the results, it was observed that Logistic Regression achieved the highest accuracy among the selected dataset.

(Chowdhury ,2020) , The objective of this paper is to evaluate multiple measurements implemented in various classifiers. Through experimentation, it is observed that Support Vector Machine (SVM) yields the most favorable outcome. Among the different kernels used under SVM, the Gaussian Radial Kernel proves to be the most effective. The proposed classifier attains an accuracy of 95% when applied to a publicly available standard ASD dataset.

(Baranwal , 2020), In this research, an ASD screening dataset is utilized to analyze and predict potential cases of ASD in adults, children, and adolescents. The dataset is examined for each age group, and conclusions are drawn based on the analysis. Various machine learning algorithms, including Artificial Neural Networks (ANN), Random Forest, Logistic Regression, Decision Tree, and Support Vector Machines (SVM), are employed for prediction and comparative purposes.

(Omar , 2019), The objective of this study is to propose an efficient prediction model utilizing machine learning techniques, specifically Random Forest-CART and Random Forest-Id3

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algorithms. The aim is to develop a mobile application capable of predicting autism spectrum disorder (ASD) in individuals of all ages. Two datasets were used for analysis, and the performance of the prediction model was compared to the mobile application based on the prediction method. The evaluation results demonstrated that the proposed prediction model outperformed in terms of accuracy, specificity, sensitivity, precision, and false positive rate (FPR) for both types of datasets.

(Usta, 2019), The aim of this study was to investigate outcome predictors using machine learning methods, employing Naive Bayes, Generalized Linear Model, Logistic Regression, and Decision Tree algorithms. The study included 433 children with a mean age of 45.9 months. Clinical Global Impression scales were assessed at baseline (T0) and at the 12th (T1), 24th (T2), and 36th (T3) months. A significant proportion of the cases demonstrated notable improvements in ASD symptoms, with 39.7% at T1, 60.7% at T2, and 77.8% at T3. The machine learning model employed in T3 indicated that the prognosis was influenced by the diagnosis group. In the autism group, advanced age of both the father and mother were found to be associated factors.

(Erkan ,2019), Datasets related to early-detected ASD were collected for individuals spanning from toddlers to adults. These datasets underwent feature transformation using techniques such as logarithmic, Z-score, and sine functions. Subsequently, various classification techniques including Adaboost, Decision Tree, Boosted Generalized Linear Model, Linear Discriminant Analysis, and Support Vector Machine were applied to these transformed ASD datasets. The results showed that Support Vector Machine (SVM) exhibited the highest performance for the toddler dataset, while Adaboost yielded the best results for the children dataset. Glmboost demonstrated superior performance for the adolescent dataset, and Adaboost remained the optimal choice for the adult datasets.

(Akter,2019), This paper aims to investigate the feasibility of utilizing Naïve Bayes, Support Vector Machine, Logistic Regression, KNN, Neural Network, and Convolutional Neural Network techniques for the prediction and analysis of ASD issues in individuals across different age groups: children, adolescents, and adults. The evaluation of these proposed techniques was conducted using three publicly available non-clinical ASD datasets.

(Abdulla,2019), The study employed three ASD datasets representing children, adolescents, and adults. To classify the ASD data, the k-Nearest Neighbors method (kNN), Support Vector Machine method (SVM), and Random Forests method (RF) were utilized. The datasets were randomly split for analysis. Results indicated that SVM and RF were effective methods for ASD classification. Notably, the RF method exhibited exceptional performance, achieving a 100% accuracy rate for all the mentioned datasets. Thus, RF emerged as the top-performing method for classifying ASD data.

(Altay, 2018) , With the growing utilization of machine learning methods, this study explored the efficacy of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) for predicting and interpreting ASD problems in children. To test these approaches, freely accessible screening datasets for autistic spectrum disorder in children were employed. By

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employing various machine learning techniques, the results unequivocally demonstrated that CNN-based prediction models outperformed other methods, providing more accurate predictions for the autistic spectrum disorder dataset.

(Maenner ,2016), This research utilized Chi-square and Least Absolute Shrinkage and Selection Operator (LASSO) as feature selection methods to identify the most significant features for three supervised machine learning algorithms: Random Forest, Logistic Regression, and K-Nearest Neighbors. The performance was evaluated using K-fold cross-validation. Among the models, Logistic Regression achieved the highest accuracy, scoring 97.541%. This result was obtained by employing the Chi-square selection method, which identified 13 key features for the model

METHODOLOGY

After the data collection process and studying the related work, the first step was the process of preparing the dataset to become suitable for the classification process for all algorithms and to give all the results and then define the algorithms with the parameters for each one and then come up with the results (Accuracy, Precision, Recall, F1-score) and find the best algorithm.

Figure1.1 shows the proposed methodology used in this study to predict autism disorder datasets. The following sections illustrate the proposed methodology.

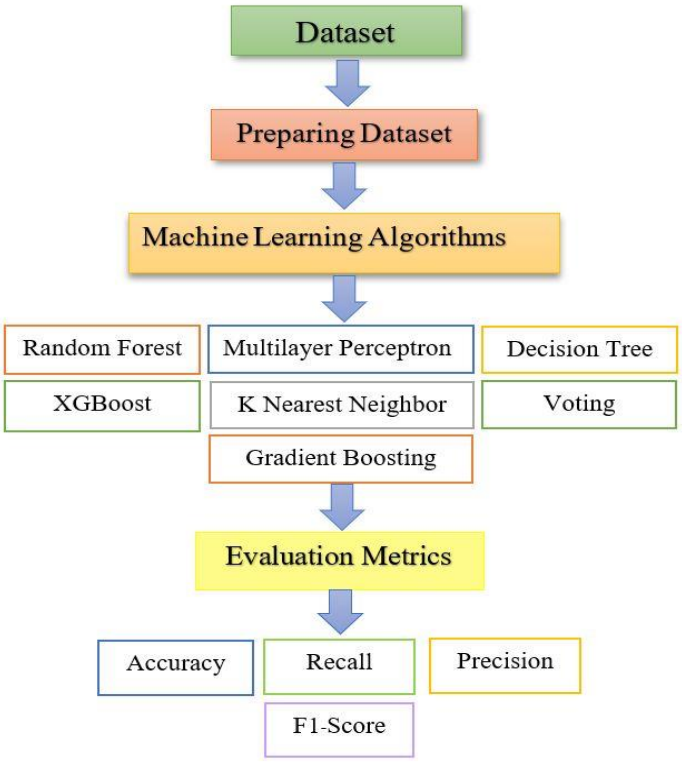

Figure 1: Research Methodology

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Dataset Description

In this paper a new dataset (shivamshine123) used containing 800 instance and 21 features with 2-classes (0 or 1) 0 classes for who having autism and 1 for not, combining and verified in hospitals and took from Kaggle datasets.

Preparing Dataset

To apply the types of machine learning algorithms in this paper to dataset, non-numerical features converted-to numerical features using a popular encoding technique. This method is known as "Label Encoder," and it turns non-numerical data into machine-readable form by replacing each value with a unique number starting at 0. three categorical features are converted to numerical using this technique: LabelBinarizer

RESULTS AND DISCUSSIONS

This section contains the evaluation metrics, the parameters for each algorithm after tuning, and the results.

Evaluation Metrics

There are several assessment measures to examine the machine learning algorithms that were utilized, including

precision, accuracy, recall, and f1-score [41]. And these are metrics' formulas regarding the following: TP =

True Positives, TN = True Negative, FP = False Positives, and FN = False Negative:

1. Accuracy: is the most intuitive performance metric, which is the ratio of properly predicted samples to the total samples, which simply is a ratio of correctly predicted samples to total samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$ (Gunawardana , 2009)

2. Precision: which is the ratio of the correctly predicted positive tweets to the total predicted positive samples.

$$Precision = \frac{TP}{TP+FP}$$ (Chinchor ,1993)

3. Recall: consider the proportion of accurately anticipated positive samples to the total number of positive samples predicted.

$$Recall = \frac{TP}{TP+FN}$$ (Lavie , 2004)

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4. F1-score: consider the weighted average of the Precision and Recall.

F1-score =2 * $\frac{\text{Precision}*\text{recall}}{\text{precision}+\text{recall}}$ (Chicco , 2020)

ALGORTHIMS

Random Forest Algorithm (RF)

A random forest is an ensemble supervised learning method used in regression and classification tasks that involves training a large number of decision trees. For the classification tasks, a prediction result is a class picked by the majority of trees. Random decision forests correct decision trees for overfitting their training set(Biau ,2016). As a result, the random forest classifier is used to classify the feature. as shown in figure 2 the algorithm works:

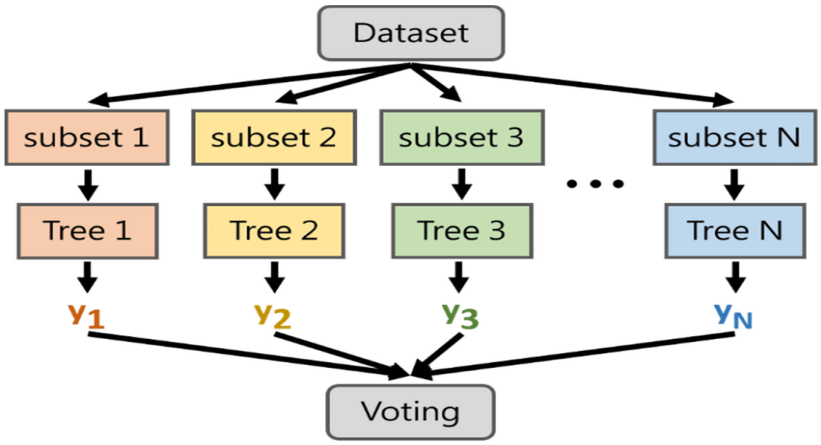

Figure 2. Random Forest

used the random forest with the classification type in this paper because the label is discrete, and the RF parameters used are as follows: n_estimators (number of decision trees) = 300, max_features = sqrt, max_depth = None, random_state = 20.

K Nearest Neighbor Algorithm (KNN)

Evelyn Fix and Joseph Hodges developed the k-nearest neighbor's method (k-NN) in 1951, which was later extended by Thomas Cover. Where It is used for data categorization and regression. In both cases, the input is a data set containing the k-closest training samples .(Guo , 2003) Depending on whether k-NN was used for classification or regression, the following results were obtained: Class membership is determined by k-NN classification. The object is classified by the majority vote of its neighbors, and it is assigned to the most common class among its k-closest neighbors (where k is a positive integer, and typically small). Where so If k = 1, we can see that item is simply assigned to the class of the item's closest neighbor. The output of kNN regression is the value of an object's property. Where This value is the average of the values of the k closest neighbors. as shown in figure 3 the algorithm works:

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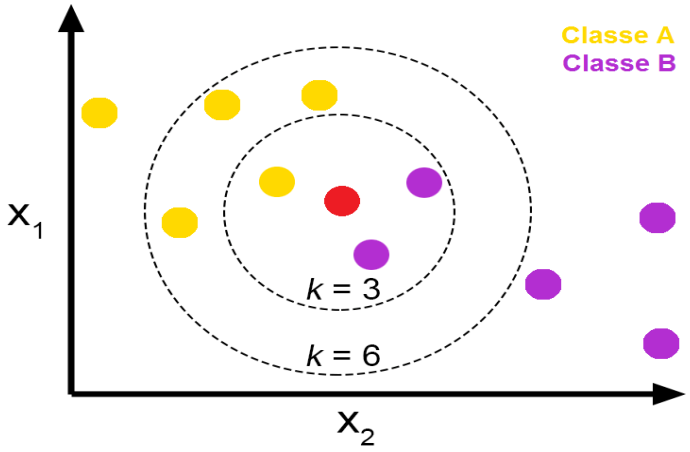

Figure 3: K Nearest Neighbor

The following points explain how KNN operates: The dataset is loaded first. In the second step, K value was set to the number of neighbors as want. In the third stage, for each data sample: For each data sample in the third stage: 1) calculate the distance between the query example and the current example using our data. 2) It adds the example's distance and index to the ordered collection. In the fourth step, sorted the ordered collection of distances and indices by distance from smallest to largest (in ascending order). Besides, we choose the first K elements from the sorted collection in the fifth phase. In the sixth step, to get labels of the selected K entries(Guo , 2018). By returning the mean of the K labels in regression and the mode of K labels in the classification (as the label in our datasets). used the KNN with classification type in our experiment because the label is discrete, and the parameters of the KNN that we used are as follows: n_neighbors= 51 and random_state = 30

Voting Algorithm

A Voting Classifier is an ensemble machine learning model that learns from a group of models and predicts an output (class) depending on the output's higher chances of being a desired class. It simply sums the results of each classifier fed into the Voting Classifier and then predicts the output class with the highest votes.

Rather than building separate specialized models to determine their performance, we propose a single model that has been trained on numerous models and predicts the output based on the cumulative majority of votes for each output class. Where Voting Classifier supports two types of voting. 1) Hard voting: the projected output class with the most votes is the one with the best chance of being predicted by each of these classifiers. 2) Soft-voting: the output class is a forecast based on an average of the likelihood provided to the class. (parhami , 1994)

The Multilayer Perceptron Algorithm (MLP)

In an artificial neural network (ANN), the multilayer perceptron (MLP) is a type of feed-forward. Whereas in some contexts, the term MLP refers to networks composed of multiple

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layers of perceptron's (with threshold activation), it can also refer to any feedforward ANN. And we can see that the term "vanilla" neural network refers to multilayer perceptron's, specifically those with a single hidden layer. An MLP has at least three-node layers: the input layer, the hidden layer, and the output layer. With the exception of the input nodes, each node is regarded as a neuron with a Nonlinear activation function (Taud , 2018) as shown in figure 4 the algorithm works:

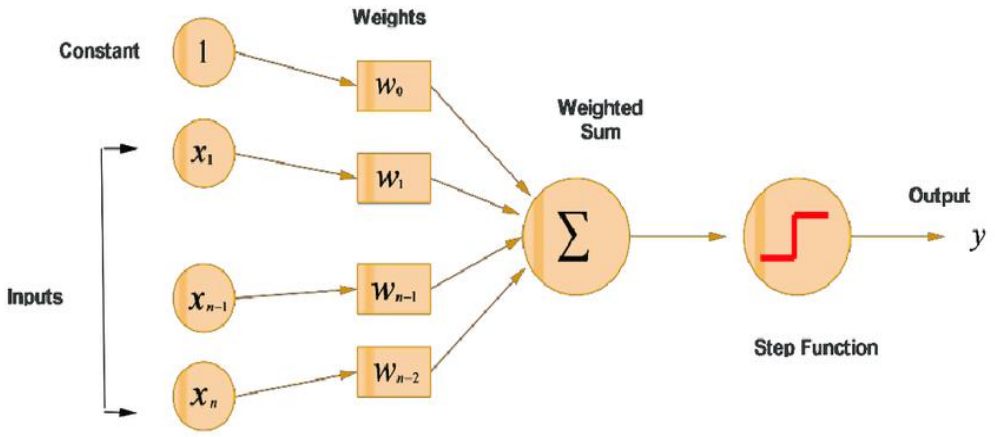

Figure 4: Multilayer Perceptron

Backpropagation is used by MLP as a supervised learning technique and during training. Furthermore, the MLP is distinguished from the linear perceptron by its multiple layers and non-linear activation. It reminds me of telling the difference between data that isn't linearly separable.

In this paper, used the MLP with classification type because the label is discrete and the parameters of MLP that are used are as the following: activation = relu and random_state = 62.

Gradient Boosting Algorithm (GB)

Gradient-boosting is a machine learning approach that, among other things, can be used for regression and classification. For weak prediction models, such as decision trees, it returns the prediction model as a group. Consider gradient boosting, which combines multiple weak learners (decision trees) into a single strong learner. Individual decision trees are poor learners in this case . Each tree in the sequence is related to the one before it, where each tree strives to correct errors of the one before it. And due to this sequential relationship, boosting the algorithms is often slow to train and yet incredibly exact. In statistical learning, the models which learn slowly perform better. And the weak learners can be fitted in such a way that each new learner fits into the residuals of a previous stage as the model improves. The final models combine the results of each phase to produce a strong learner. To detect residuals, a loss function is used. For example, in regression work, the Mean Squared Error (MSE) can be used, whereas, in classification work, logarithmic loss (log-loss) can be used. It's worth noting that nothing changes when a new tree is added to the model (Bentejac ,2021). as shown in figure.5 the algorithm works:

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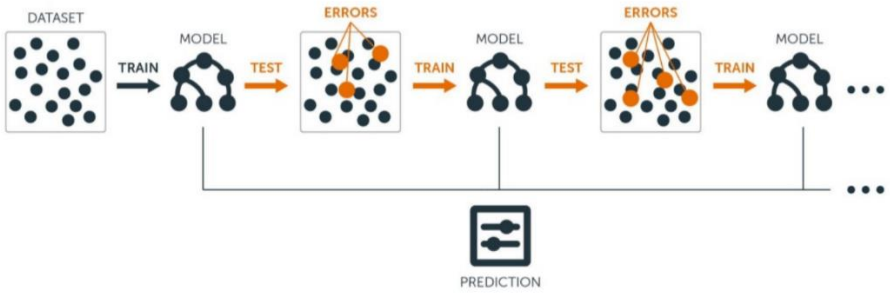

Figure 5: Gradient Boosting

The added decision tree then fits the residuals of the current model. We used the GB with classification type in our experiment because the label is discrete, and the GB parameters we used are as follows: subsample= 1.0, learning_rate = 0.1, criterion= friedman_mse, n_estimators = 100,

and random_state = 40.

The Decision Tree Algorithm (DT)

A decision tree is administered by a machine learning algorithm that makes judgments based on a set of rules, similar to how people do. Decision tree learning, also known as stimulation of the decision trees, is one of the predictive modeling methodologies and used in three fields: statistics, data mining, and machine learning . Where it goes from the observations and about a sample (represented in branches) to the inferences about the sample's target value by using the decision tree Classification trees are tree models with a discrete target variable; within these tree structures, the leaves represent class labels , while the branches represent features in the dataset, allowing the class labels to be predicted. Decision trees with a continuous target variable (typically real numbers) are known as regression trees. Whereas decision trees are important in terms of comprehensibility and simplicity, they are one of the most well-known machine learning algorithms.(Charbuty , 2021). as shown in figure.6 the algorithm works:

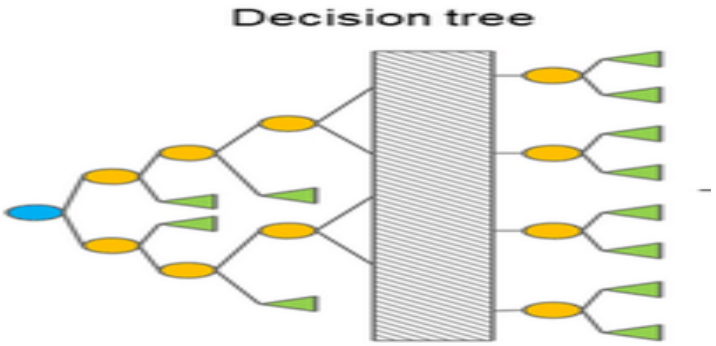

Figure 6: Decision Tree Algorithm

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We used the Decision Tree with classification type in our experiment because the label is discrete, and the DT parameters we used were criterion = entropy and random_state = 42.

Xtreme Gradient Boosting Algorithm (XGBoost)

Extreme Gradient Boosting Means abbreviated as XGBoost is used for classification and regression tasks. XGBoost have been made to parallelize and optimize the gradient boosting algorithm. By parallelizing the entire boosting procedure, the training time, which was initially substantial, has been significantly reduced. Unlike traditional approaches that focus on creating the best model on the data, our approach involves training numerous models on different subsets of the training dataset and selecting the best-performing model through voting. XGBoost often surpasses conventional gradient boosting methods in terms of performance. The Python implementation provides access to a wide range of internal parameters that can be adjusted to enhance precision and accuracy.. [19]

This algorithm's general function is to convert weak learners (decision trees) into strong learners, which means that the strong learner generates the final prediction label (average of each prediction by week classifier). The XGBoost has several significant features:

1) Parallelization: The model is designed to run simultaneously on several CPU cores.
2) Regularization: XGBoost offers a variety of regularization penalties to prevent overfitting. Regularizations with penalties result in training, allowing the model to generalize successfully.
3) The Non-Linearity: Is the ability of the XG-Boost to recognize and learn from Non-Linear data patterns.
4) Cross-validation is builtin where it is immediately available.
5) Scalability: XGBoost can run distributed, by allowing you to manage huge capacities of data,

(Li,2019). as shown in figure.6 the algorithm works:

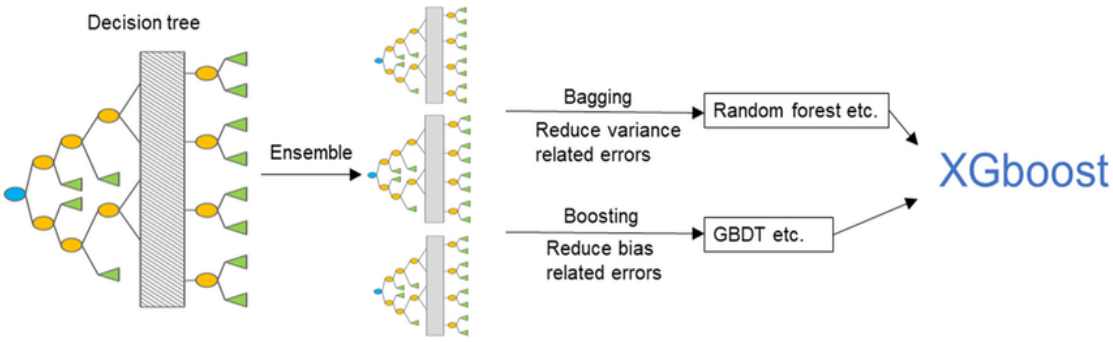

Figure 7: Xtreme Gradient Boosting

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In this experiment, we used the this algorithm with classification type because the label is discrete and the parameters of XGBoost that used are as the following: colsample_bylevel = 1, the learning_rate = 0.1, the gamma = 0, the n_estimators = 100, and the random_state = 22.

Binary Classification experiment

In this experiment, machine learning algorithms were applied to detect if this sample in the dataset was with autism or not. As shown in **Table 2**, the performance results for machine learning algorithms used depend on four metrics: precision, accuracy, recall, and f1-score All algorithms. All algorithms achieved higher performance results in these metrics when we selected all features in the detection process.

Table 1: performance results

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.993	0.994	0.995	0.994
K-Nearest Neighbor	0.993	0.991	0.990	0.991
Voting algorithm	0.992	0.993	0.993	0.994
Multilayer Perceptron	0.992	0.993	0.996	0.995
Gradient Boosting	0.990	0.989	0.988	0.989
Decision Tree	0.993	0.995	0.992	0.993
XGBoost	0.994	0.997	0.997	0.996

After applying the data set on the algorithms, the results shown in table 2 that tha XGboost

Algorithm give the best result in terms of (accuracy, precision, recall, F1-score), the iterative (repetition) And overlapping made the XGboost better specially the parallelization process made

The efficiency increase with the presence of the cross-v as the selection of the best values, then

The boot process was distributed to the CPU- cores in parallel.

CONCLUSION AND FUTURE WORK

This study looked at how different machine learning algorithms (KNN, RF, XGB, DT, MLP, GB, and voting) performed on new autism datasets: shivamshine123. In this dataset, conducted the experiments: binary classification. used four popular evaluation metrics to assess performance for these algorithms: precision,

accuracy, recall, precision, and f1-score. Where the performance results in the dataset are as follows: all algorithms achieved close performance results in the experiment. The results indicated that the XGBoost algorithm are highly good at detecting autism with the four evaluation metrics . in the future , the plan is to apply more machine learning algorithms, pre-trained models, and deep learning algorithms to another autism dataset.

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