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Laplace Kernel Quadratic Segmented Regressive Federated Learning for ASD Prediction

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Abstract — **Autism Spectrum Disorder (ASD) is neurodevelopmental anarchy typified through range of challenges at social interaction, communication, monotonous behaviors affecting individuals across different age groups, comprising toddlers, and so on. Efficiency and accuracy of ASD prediction are improved by using Machine Learning (ML) algorithms. Early detection of ASD poses additional challenges due to its complexities. To address this issue, the Laplace Kernel Quadratic Segmented Regressive Federated Learning (LKQSRFL) technique is proposed to enhance the accuracy of ASD detection while minimizing time consumption. Furthermore, the proposed LKQSRFL technique encompasses key processes, including data acquisition, preprocessing, and ASD prediction. Moreover, the data obtained from the dataset comprises four distinct datasets related to individuals from different age groups. Additionally, the data can be preprocessed by removing redundant data from the dataset and converting the raw data into a suitable format. After that, by analyzing and testing the training and data models, the segmented regression gradient federated learning (RGFL) approach can be used to detect individuals with ASD characteristics or without ASD. Furthermore, the ASD prediction accuracy, prediction time, precision, recall, sensitivity, and F1 score are considered to determine the test score. The results show that the proposed LKQSRFL method achieves effective performance results with the best accuracy increasing to 98.05% through reduced prediction time.**

Keywords— autism spectrum disorder (ASD) detection, Weighted Proximal multivariate imputation, Lexis ratio statistical method, Peirce's criterion-based outlier detection, Laplace kernelized quadratic multivariate discriminant method, segmented regressive gradient Federated Learning

I. INTRODUCTION

ASD represents multifaceted and diverse range of neurodevelopmental conditions that impact individuals across various age groups. Due to the unique characteristics and challenges, ASD poses a significant concern. Premature recognition as well as accurate diagnosis of ASD are pivotal for implementing timely interventions and support. Numerous ML methods have designed at autism spectrum disorder detection. Artificial Neural Network (ANN) model was introduced in [1] with aim of attaining enhanced accuracy in ASD detection. But, the simultaneous learning of features and accurate classification were difficult particularly when applying larger datasets. A Random Forest (RF) classifier was developed [2] to analyze and predict ASD in toddlers as well as adolescents, utilizing non-clinical ASD datasets. However, the issue of time consumption in ASD prediction remained unresolved.

Clinical gait analysis was conducted in [3] for children through ASD. However, ML techniques were not employed to enhance performance. A Multilayer Perceptron (MLP) classifier was developed in [4] to automate the diagnosis process using ASD database for toddlers, and so on. However, it faced limitations in collecting extensive database as well as working by DL techniques which incorporate feature evaluation and classification to enhance accuracy of ASD prediction. Early recognition of ASD Strategy was introduced [5]. However, it faced challenges in utilizing techniques such as machine learning for accurate predictions of ASD traits. A ML models were designed [6] for ASD classification.

The World Health Organization estimates that one in 160 children has ASD. Some individuals with autism require support and care to live independently. These symptoms appear in childhood and persist into adulthood. The exact cause of ASD is still under investigation, although a combination of genetic factors and environmental influences may activate those genes [7-8]. Early detection of disability is an essential step in addressing the problem and enables preventive measures. However, these studies failed to establish a connection between the underlying practices and such tools [9-10]. A lack of qualified personnel and insufficient resources creates logistical challenges to access.

A. The Contribution of The Research

- To improve the accuracy of forecasting ASD across all age groups, the LKQSRFL method is developed, incorporating both preprocessing and prediction.
- To minimize ASD forecast time, the LKQSRFL technique addresses missing data imputation by employing weighted proximal multivariate imputation.
- After data acquisition, the next step involves preprocessing, which includes cleaning and transforming the raw data into an appropriate format. This essential stage ensures that the data is organized and ready for analysis, enhancing the quality and reliability of the dataset.

- The Lexis ratio statistical method is used to eliminate noisy data from the dataset effectively. Additionally, the LKQSRFL method is utilized to obtain dimensionality-reduced features for accurate ASD prediction.
- The LKQSRFL technique employs segmented regressive gradient Federated Learning to enhance accuracy and precision in ASD prediction. The Levenberg–Marquardt algorithm is applied to minimize squared loss in ASD prediction.
- Lastly, extensive experiments were conducted to evaluate the results of the LKQSRFL method in comparison to other relevant works.

B. Structure of paper

Manuscript is organized as follows: Section 2 appraisal literature review. In Section 3, the LKQSRFL method is explained through comprehensible diagram. Section 4 provides experimental settings as well as gives dataset explanation. A comparative analysis of dissimilar methods is presented in Section 5. Lastly, Section 6 summarizes the manuscript.

II. LITERATURE REVIEW

Several ML techniques were designed for recognition of ASD in [11]. However, these techniques failed to achieve higher accuracy in ASD detection. A ML model was presented [12] through aspire of enhancing accuracy of ASD identification across various age levels. The model incorporated several feature selection techniques but more efficient ASD diagnosis system was not developed. Ensemble comprising RF and XGBoost classifiers was developed [13] for precise detection of ASD.

ML techniques and trained RF methods were developed in [14] to predict ASD diagnoses. However, these models proved inefficient when dealing with large databases. A set of ensemble techniques was developed in [15] to enhance ASD prediction performance. However, the designed technique failed to provide the best results in predicting ASD. AI and the IoT were introduced [16] for recognition of ASD. A modified bat method depend on ANN was developed in [17] to enhance ASD detection. However, the assessment of the severity of ASD was not conducted.

A support vector machine was developed in [18] for automated autism spectrum disorder detection. A at Federated Learning method was developed in [19] for premature diagnosis of ASD through enhanced accuracy. However, severity of ASD remained unaddressed through deep learning methods. A hybrid classifier, combining SMO with SVM, was developed [20] to improve accuracy of ASD recognition. However, classifier faced limitations as it did not incorporate dimension reduction methods to reduce the time required for ASD detection.

III. PROPOSAL METHODOLOGY

Autism is neurological as well as developmental anarchy that impacts neural function at brain. It is a complex condition characterized by different neural functioning. Individuals with autism often display variations in social interaction and so on. Detection of ASD presents a range of challenges.

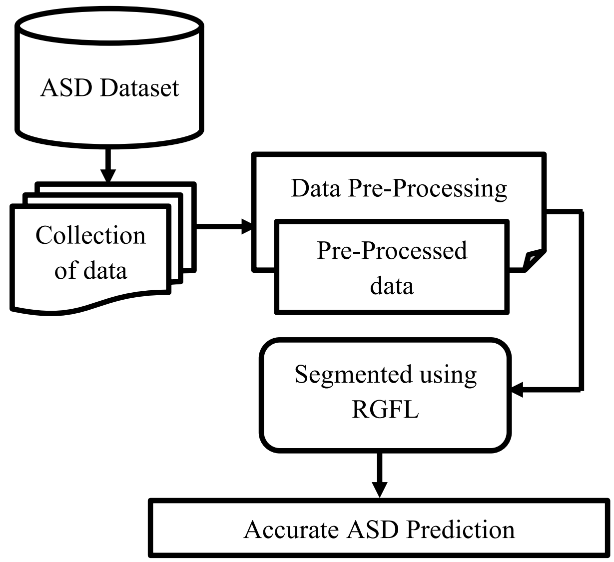

Fig 1. structural design of LKQSRFL technique

The LKQSRFL technique is employed for detection of ASD. Various processes involved in ASD detection, depicted with a clear architecture, as illustrated in Figure 1. Furthermore, depicts overall structural design of LKQSRFL technique that includes three stages such as data collection, preprocessing and ASD detection.

A. Data collection

It is fundamental process of collecting information and raw information as of database related to different age group individuals for ASD detection analysis. In the proposed LKQSRFL technique, data related to different age groups namely Toddler, and so on are collected from the four publicly available ASD screening dataset.

B. Data Preprocessing

It is fundamental step at data analysis which includes cleaning as well as transforming raw dataset to format for analysis or modeling to improve quality, accuracy, effectiveness of information for ASD detection study. There is different key steps involved in data preprocessing such as missing data handling, noisy data removal and outlier data detection.

a. Missing data handling

Handling missing data is basic step in data preprocessing step. It occurs when there are no data values for certain variables or features in a dataset. Therefore, the missing data handling is used to address accurate analyses of ASD detection. Weighted Proximal multivariate imputation method is applied in the proposed LKQSRFL method for estimating missing values based on the values of nearest neighbors in dataset.

Let us consider the input dataset 'DS' in form of matrix as given below equation 1.

$$\begin{bmatrix} F_1 & F_2 & \dots & F_m \\ S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{m1} & S_{m2} & \dots & S_{mn} \end{bmatrix} \quad (1)$$

Where, 'I' indicates a input matrix, the data samples 'S' are presented in the row and the features or attributesF_1 , F_2, ... F_m are organized in the column of the dataset respectively. Formula for calculating the missing value is given below equation 2,

$$S_M = \frac{\sum_{m=1}^{K} \vartheta_m S_{mn}}{\sum_{m=1}^{k} \vartheta_m} \quad (2)$$

Where, S_M denotes an imputed value, S_{mn} denotes a value of the m^{th} nearest neighbor data samples, ϑ_m denotes a weight assigned to the nearest neighbor. Replace the missing value with the computed value. This process is repeated for each missing value in the dataset.

C. Noise data removal

Removing the noise data from dataset is a common preprocessing step to improve the overall accuracy of a model. Noise in the data direct to inaccurate ASD predictions and removing of these data helps in obtaining more reliable results. It is identified that data that contains random variations from the overall data samples. The proposed LKQSRFL technique utilizes the Lexis ratio statistical method to measure variance of the sample proportion. The ratio is defined as follows, as below equations 3 and 4.

$$LR = \left(\frac{Var^2}{d^2}\right) \quad (3)$$

$$Var = \sum_{j=1}^{m} \left|S_i - S_j\right| \quad (4)$$

Where, LR denotes a Lexis ratio statistical method, S_i denotes a current data point, S_j denotes another data points in the particular feature, m indicates a number of data points in the specific aspect, Var denotes a variance the data points, d indicates a deviation from the expected value. From the analysis, the Lexis ratio provides the output ranges from the 0 to 1. If the Lexis ratio is greater than maximum allowable deviation, afterward data point is normal. Or else, data point is called as noisy information points. These data points are detached as of database.

D. Outlier data handling

Outlier recognition is process of recognizing data point at database which diverge considerably as of overall distribution of other information points. Peirce's criterion is used for finding the outlier to improve the quality and robust modeling.

The formula for calculating the Peirce's criterion is give below equations 5 and 6.

$$D = |S_i - S_m| \quad (5)$$

$$S_m = \frac{\sum_{i=1}^{n} S_i}{n} \quad (6)$$

Where, S_i denotes a data sample, S_m denotes a mean of the data samples, OD indicates an Outlier detection, D indicates a deviation. The following criterion is used to detect the outlier in the distribution of the data samples, as below equation 7.

$$y = \begin{cases} max\ D < D, OD \\ otherwise, ND \end{cases} \quad (7)$$

Where, y denotes a outcome, $\max D$ denotes maximum allowable deviation. If deviation for information point is superior than maximum allowable deviation, afterward it considered outlier data. Or else, data point is normal. Based on this analysis, outlier information points are detached for further processing.

E. Dimensionality reduction

It is method employed in data analysis to minimize number of input features at database. The main aim is to simplify the dataset while retaining its essential information. The dataset has a large number of features, poses a challenges in terms of computational efficiency. The relevant feature selection procedure involves selecting subset of pertinent aspect while discarding others as of dataset.

Therefore, Laplace kernelized quadratic multivariate discriminant method is applied in the proposed LKQSRFL technique for dimensionality reduction by selecting the relevant attributes. A Laplace kernelized quadratic multivariate discriminant is ML method that divides input into two classes based on 'm' features (i.e. multivariate).

Let us consider number of input independent variables i.e. features F_1 , F_2, ... F_m taken as of database.

First define the two types of class's i.e. relevant or irrelevant classes. After defining the class, the mean is computed.

The mean vector for each class 'M_k' is computed as given below equation 8,

$$M_k = \frac{1}{m}\sum_{j=1}^{m} F_j \quad (8)$$

Where, M_k denotes a mean vector, m is number of features in class as well as F_j is feature vector in class. Then apply the Laplace kernel function to measure the likelihood or covariance between the features and mean vector. As shown in equation 9.

$$V_k = exp\left[-\sum_{i=1}^{n}\left(\frac{F_j - M_k}{\sigma}\right)\right] \quad (9)$$

Where, V_k indicates the covariance between the features ($F_1, F_2, \ldots F_m$) and mean vector M_k, σ indicates a standard deviation.

After that, the discriminant score is computed as follows, as below equation 10.

$$\delta_c = -\frac{1}{2}\log|V_k| - \frac{1}{2}(F_j - M_k)^T \frac{1}{|V_k|}(F_j - M_k) + log(p_k) \quad (10)$$

Where, δ_c denotes an estimated discriminant score, $|V_k|$ indicates a determinant of the covariance matrix, p_k denotes a prior probability that an observation belongs to k^{th} class. As a result, the features are separated into k^{th} class for which discriminant score is largest, as below equation 11.

$$Z = argmax\delta_c \quad (11)$$

Where, Z indicates an output function, $\arg max$ represent argument of maximum function, δ_c denotes a discriminant score.

Algorithm 1: data preprocessing

Input: Datasets 'DS', Sample instances '$S = \{S_1, S_2, \ldots, S_n\}$', Features '$F = \{F_1, F_2, \ldots, F_m\}$'

Output: Preprocessed dataset

Begin

Collect the number of features "$F = \{F_1, F_2, \ldots, F_m\}$", samples instances $S = \{S_1, S_2, \ldots, S_n\}$ from the dataset

Construct input matrix 'I' using (1)

For each features 'F' and instances 'S'

Handle missing value using (2)

End for

For each data point S_i and S_j

Apply Lexis ratio using (3)

Find the noisy data

end for

Apply Peirce's criterion using (3)

if ($\max D < D$) **then**

Outlier data points

else

Normal data points

end if

For each feature in input matrix

Initialize the number of classes 'k'

For each class

Compute the Mean vector 'M_k'

Apply Laplace kernel to measure covariance using (9)

Compute the discriminant score using (10)

Find largest discriminant score using (11)

Return (relevant and irrelevant features class)

Select relevant features and remove other features

End

Algorithm 1 sketch data preprocessing steps aimed at improving the autism prediction while minimizing time consumption. Procedure begins through gathering input aspect and sample instances as of database containing individuals across various age groups. Subsequently, missing data is imputed using the Weighted Proximal Multivariate Imputation method. Following imputation, a Lexis ratio statistical method is applied to identify noisy data, assessing the variance within the samples. Next, Peirce's criterion is employed to detect outlier data points. This step aids in recognizing examination which diverge considerably as of entire database. Lastly, dimensionality reduction is carried out using the Laplace Kernelized Quadratic Multivariate Discriminant method. This technique is utilized to distinguish pertinent as well as immaterial features in database, enhancing efficiency of subsequent autism prediction models.

F. segmented regressive gradient Federated Learning

Finally, the autism prediction is performed with the selected relevant features using FL. It is decentralized ML method which permits method training across multiple sample instances. This decentralized approach involves local training as well as global aggregation methods. In the local training model, Sokal–Sneath indexive segmented regression is used for analyzing the sample instances and classifying the ASD presence and absence of individual. Locally updated methods are after that integrated as well as fed to global aggregation method to obtain accurate ASD prediction.

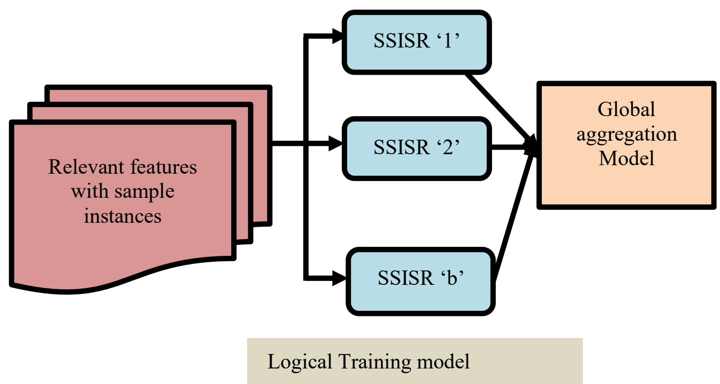

Fig. 2. Segmented using RGFL

Figure 2 depicts the procedure of the Sokal-Sneath indexive segmented regressive FL. This learning method considers input, specifically the number of data sample instances. Method initialises 'b' number of local training techniques, namely Sokal–Sneath indexive segmented regression (SSISR). SSISR is a machine learning algorithm in which the dependent variable, i.e., sample instances, is segmented into two categories, namely the presence of ASD and the absence of ASD.

Let us consider the number of sample instances $S = \{S_1, S_2, \ldots, S_n\}$ taken from the dataset related to four age groups of peoples. Then the Sokal–Sneath index function is utilized for measuring association among testing and training sample instances. Relationship between the sample's instances are estimated as follows, as equation 12.

$$Q = \frac{|S_{ts} \cap S_{tr}|}{(S_{ts} \cup S_{tr}) + (S_{ts} \Delta S_{tr})} \quad (12)$$

Where, Q indicates a Sokal–Sneath similarity coefficient, S_{ts} denotes the testing sample instances , S_{tr} shows the training sample instances, $S_{ts} \cap S_{tr}$ indicates a mutual dependence between the two sample instances, $S_{ts} \cup S_{tr}$ denotes a mutual independence between the two sample instances, $S_{ts} \Delta S_{tr}$ indicates a variance between the two sample instances . The similarity coefficient (Q) provides the output value between [0, 1]. Based on the similarity value, the regression function partitions the sample instances into two classes namely presence of ASD and absence of ASD.

Then locally trained classification outcomes are integrated in global aggregation method. So, weighted averages of local trained methods are computed as below equation 13.

$$W = \frac{1}{b} \sum_{j=1}^{b} r_j L_j \quad (13)$$

Where, W indicates global aggregator model, r_j denotes weight of local trained method 'L_j', b represents number of local models.

Global aggregation model utilizes the Levenberg–Marquardt algorithm is to reduce the squared loss of local training model as follows, as equations 14 and 15.

$$f = argmin[loss(L_j)] \quad (14)$$

$$loss\ (L_j) = [A - O_r]^2 \quad (15)$$

Where, f denotes an objective function of aggregation model, $arg\,min$ denotes an argument of minimum function, $loss\ (L_j)$ denotes a loss of local training model, A dentoes an actual classification results, Or denotes an observed classification result. In order to minimize the error, the proposed federated learning model utilizes the gradient function for updating the weights, as shown in equation 16.

$$r_{j+1} = r_j - \eta \left[\frac{\partial\ loss\ (L_j)}{\partial r_j}\right] \quad (16)$$

Where, r_{j+1} represents updated weight, r_j denotes current weight, η indicates a learning rate , $\frac{\partial\ loss\ (L_j)}{\partial r_j}$, symbolize partial derivative of loss '$loss\ (L_j)$' with current weight 'r_j'. The procedure is iterated until it attains minimum loss. Lastly, global aggregation method gives last classification results with minimal loss. The algorithm of segmented regressive gradient Federated Learning is given below,

// Algorithm 2: segmented regressive gradient Federated Learning

Input: preprocessed Dataset, number of selected features $\{F_2, F_3 \dots . F_k\}$ and data samples instances $S_1, S_2, S_3 \dots . S_n$

Output: enhance the autism spectrum disorder prediction accuracy

Begin

1: Initialize learning rate 'η', number of local models 'b', number of iterations 'T'

2: Construct 'b' number of models with data samples instances

3: **for each** training sample and testing sample

4: Measure the similarity using (12)

5: Classification results are obtained

6: **end for**

7: **Combined the** Trained model with Weighted average using (13)

8: Define the objective function for local training model using (14)

9: Update the weight r_{j+1} using (16)

10: Go to step 7 until reaches the iterations

11: **Return** (**Samples** detected with ASD traits and no ASD traits)

End

Algorithm 2 illustrates the various steps involved in predicting autism spectrum disorder with higher accuracy using Federated Learning. FL procedure is initiated through constructing set of local training methods. In these models, the similarity between testing and training data is analyzed. Afterward, global aggregation method combines outcomes attained as of local methods and assigns weights. Subsequent this, method assigns objective function to every local training method. To reduce loss of classification, initially assigned weights are updated with gradient function. This procedure is iterated till it attains maximum iteration. Lastly, accurate prediction outcomes are obtained

IV. EXPERIMENTAL SETUP

Experimental evaluation of LKQSRFL and conventional ANN model [1], as well as the RF classifier [2], is executed by Python. To perform experiment, datasets from four different age groups have been collected from Kaggle and the UCI Machine Learning Repository. The ASD screening database are obtained from sources [21], [22], [23], and [24] for experimental analysis. The combination of these four datasets is utilized as input for ASD prediction.

TABLE I. DATA DESCRIPTION

S. No	Dataset	Number of Features	Number of sample instances
1	Toddler's	19	1054
2	Child	21	292
3	Adolescent	21	104
4	Adult	21	704

Table 1 reveals that a total of 2154 combined sample instances were employed for conducting the simulation. To evaluate performance, sample instances ranging from 200 to 2000 were chosen as of database.

A. Results

Experimental assessment of LKQSRFL as well as conventional mordels are estimated through different performance parameters across dissimilar sample instances.
Discussion

The experimental results are clearly shown in comparison with the previous RF and ANN techniques to highlight the improvements in the proposed LKQSRFL technique for detecting ASD.

TABLE II. SIMULATION PARAMETER

Simulation	Variable
Dataset Name	ASD Dataset
Number of sample instances	2000
Training	1,357
Testing	643
Language	Python
Tool	Jupyter

The dataset, known as the "ASD Dataset," comprises 2000 samples, with 1,357 allocated for training and 643 for testing. Implemented via Python in Jupyter, these parameters outline the dataset's scope and tools used, as shown in Table 2.

ASD prediction accuracy: It is defined ratio of number of samples instances correctly predicted as an ASD or not as of total number of samples. So, it is expressed as below, equation 17.

$$\boldsymbol{ASD_{ACC} = \sum_{i=1}^{n} \frac{S_{AD}}{S_i} * 100} \quad (17)$$

Where, $\boldsymbol{ASD_{acc}}$ denotes an ASD prediction accuracy, $\boldsymbol{S_{AD}}$ samples precisely forecast with ASD traits, $\boldsymbol{S_i}$ denotes a total number of samples. It is calculated in percentage (%).

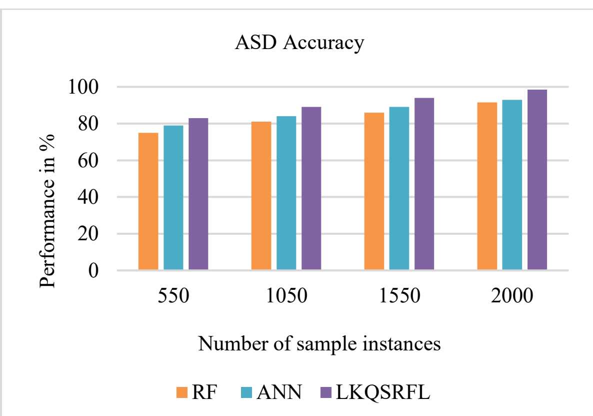

Fig. 3. Evaluation Results of ASD Accuracy

As illustrated in Figure 3, the accuracy analysis reveals that the proposed LKQSRFL method outperforms the previous RF and ANN methods. The LKQSRFL method achieves an accuracy of 98.05% in detecting ASD. In comparison, the accuracy rates for the previous RF and ANN methods are 93% and 91.5%, respectively.

Precision: It is the classification metrics that measures the performance of true positives and false positives through ASD prediction. It is formulated below equation 18.

$$PR = \left(\frac{TP}{TP+FP}\right) \quad (18)$$

Where, PR represents a Precision, TP symbolizes true positive, FP represents false positive.

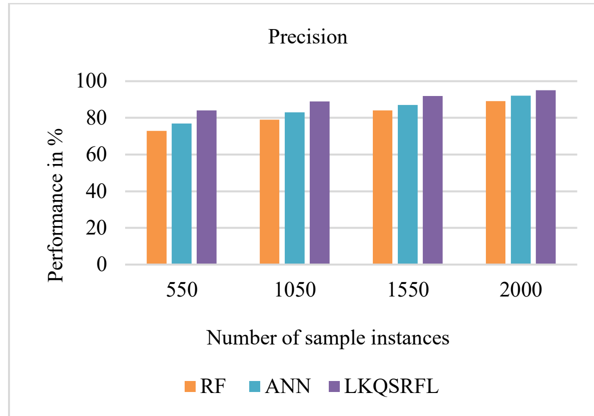

Fig. 4. Analysis of Precision

As shown in Figure 4, the precision analysis of the proposed LKQSRFL method and the previous RF and ANN methods indicate that the experimental results are better. Furthermore, the precision performance ratio of the proposed LKQSRFL method is shown to be 95.11% and it detects ASD. Similarly, the precision performance ratio of the proposed method and the previous RF and ANN methods are described as 89.14% and 92.15% respectively.

Sensitivity: The Sensitivity also known as Recall which is measured based on number of true positives and false negatives through ASD prediction. It calculated below equation 19,

$$Sen = \left(\frac{TP}{TP-FN}\right) \quad (19)$$

Where 'Sen'indicates a sensitivity, Tr_p represents true positive, Fl_n symbolize false negative.

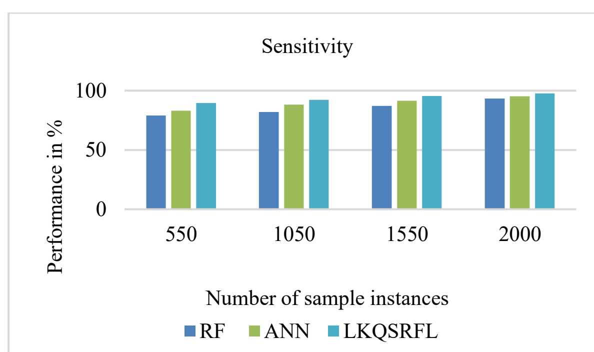

Fig. 5. Analysis of Sensitivity

The sensitivity comparison between the suggested LKQSRFL approach and the earlier RF and ANN methods shows that the experimental results are superior, as shown in Figure 5. Additionally, it is demonstrated that the suggested LKQSRFL method detects ASD with a sensitivity performance ratio of 0.988%. Comparably, the proposed method's sensitivity performance ratio and that of the earlier RF and ANN approaches are 0.934% and 0952%, respectively.

F1- score: it is a metric that combines performance of both PR and recall. It is expressed as below equation 20.

$$\boldsymbol{F1-score = 2 * \left[\frac{PR*Sen}{PR+Sen}\right]} \quad (20)$$

Where, $\boldsymbol{PR}$ indicates precision, $\boldsymbol{Sen}$ represents a sensitivity or recall.

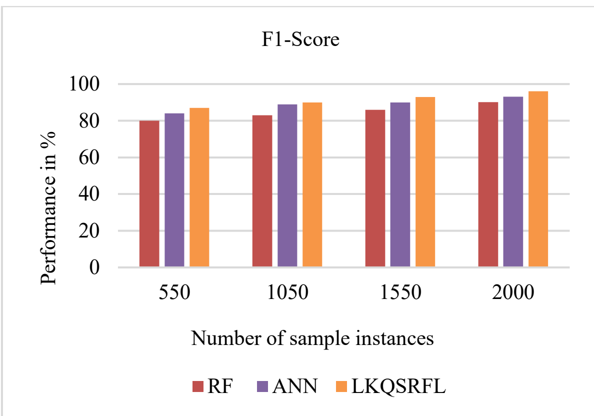

Fig 6. Analysis of F1-Score

As shown in Figure 6, the F1-score analysis comparing the proposed LKQSRFL method with previous RF and ANN methods demonstrates superior results. The LKQSRFL method achieves an F1-score of 96.12%, indicating its effectiveness in ASD detection. Additionally, the F1-scores for the proposed method and the earlier RF and ANN methods are reported as 90.14% and 93.06%, respectively.

ASD prediction time: it is computed as amount of time utilized through method for ASD prediction. It is expressed as below equation 21.

$$ASD_{time} = \sum_{i=1}^{n} S_i * Time(ASD\ prediction) \quad (21)$$

Where, ASD_{time} denotes an ASD prediction time based on the sample instances 'S_i' and actual time utilized in ASD prediction '$Time\ (ASD\ prediction)$'. It is computed in milliseconds (ms).

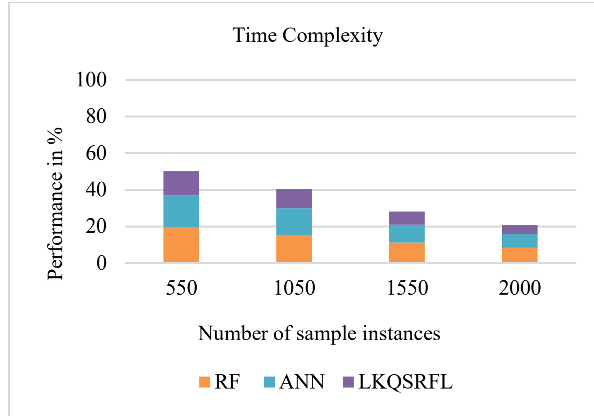

Fig. 7. Analysis of Time Complexity

The time complexity analysis comparing the suggested LKQSRFL method with earlier RF and ANN methods shows better results, as seen in Figure 7. With a time-complexity of 4.8 ms, the LKQSRFL approach demonstrates its efficacy in detecting ASD. Furthermore, the suggested method's time complexity is 8.4 ms, whereas the preceding RF and ANN approaches have a time complexity of 7.5 ms.

V. CONCLUSION

In conclusion, the LKQSRFL technique has been proposed to significantly enhance the accuracy of ASD detection while minimising the time consumption associated with predictions. The key advantage of the LKQSRFL approach lies in its ability to provide high-accuracy results while reducing the computational time, making it both practical and efficient for real-world applications. The dataset used in this paper comprises four distinct sub-datasets, each representing individuals from a different age group. This method analyses both the training and testing data models, allowing for a reliable classification of ASD cases. Key performance metrics, including accuracy, prediction time, precision, recall, sensitivity, and F1 score, are used to evaluate the model's effectiveness. The results demonstrate that the LKQSRFL method outperforms traditional machine learning models such as RF and ANN in ASD detection. The LKQSRFL technique achieved an impressive accuracy rate of 98.05%, a significant improvement over the RF model (93%) and the ANN model (91.5%). Moreover, this accuracy is achieved with reduced prediction time, enhancing the overall efficiency of the detection process.

A. Future Research

- Future research may aim to incorporate real-world data from various sources to improve the generalisation of ASD detection models.
- The ability to consider data from diverse areas, demographics, and clinical conditions enables

researchers to ensure that the model will be effective in various settings and conditions.

REFERENCES

[1] Rownak Ara Rasul, Promy Saha, Diponkor Bala, S.M. Rakib Ul Karim, Md. Ibrahim Abdullah, Bishwajit Saha, "An evaluation of machine learning approaches for early diagnosis of autism spectrum disorder", Healthcare Analytics, Elsevier, 2024, Pages 1-20. https://doi.org/10.1016/j.health.2023.100293

[2]Jyotismita Talukdar, Deba Kanta Gogoi, Thipendra P. Singh, "A comparative assessment of most widely used machine learning classifiers for analysing and classifying autism spectrum disorder in toddlers and adolescents", Healthcare Analytics, Elsevier, Volume 3, 2023, Pages 1-16. https://doi.org/10.1016/j.health.2023.100178

[3] Xinye Wu, D. Clark Dickin, Laura Bassette, Caroline Ashton, He Wang, "Clinical gait analysis in older children with autism spectrum disorder", Sports Medicine and Health Science, Elsevier, 2023, Pages 1-5. https://doi.org/10.1016/j.smhs.2023.10.007

[4] Md Delowar Hossain, Muhammad Ashad Kabir, Adnan Anwar and Md Zahidul Islam, "Detecting autism spectrum disorder using machine learning techniques", Health Information Science and Systems, Volume 9, Issue 1, Pages 1-13. doi: 10.1007/s13755-021-00145-9

[5] Roula Choueiri, William T. Garrison, Valerie Tokatli, "Early Identification of Autism Spectrum Disorder (ASD): Strategies for Use in Local Communities", Indian Journal of Pediatrics, Springer, Volume 90, 2023, Pages 377–386. https://doi.org/10.1007/s12098-022-04172-6

[6] Daniela, Nicholas Dominica, Tjeng Wawan Cenggorob, Bens Pardamean, "Machine Learning Approaches in Detecting Autism Spectrum Disorder", Procedia Computer Science, Elsevier, Volume 227, 2023, Pages 1070-1076. https://doi.org/10.1016/j.procs.2023.10.617

[7] D. Pavithra, A. N. Jayanthi, "An improved adaptive neuro fuzzy interference system for the detection of autism spectrum disorder", Journal of Ambient Intelligence and Humanized Computing, Springer, Volume 12, 2021, Pages 6885–6897. https://doi.org/10.1007/s12652-020-02332-0

[8] Fawaz Waselallah Alsaade and Mohammed Saeed Alzahrani, "Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms", Computational Intelligence and Neuroscience, Hindawi, Volume 2022, February 2022, Pages 1-10. https://doi.org/10.1155/2022/8709145

[9] Ashima Sindhu Mohanty, Priyadarsan Parida & Krishna Chandra Patra, "ASD detection using an advanced deep neural network", Journal of Information and Optimization Sciences, Volume 43, Issue 8, 2022, Pages 2143-2152. https://doi.org/10.1080/02522667.2022.2133220

[10] Anders Dechsling, Frederick Shic, Dajie Zhang, Peter B. Marschik, Gianluca Esposito, Stian Orm k , Stefan Sütterlin, Tamara Kalandadze, Roald A. Øien, Anders Nordahl-Hansen, "Virtual reality and naturalistic developmental behavioral interventions for children with autism spectrum disorder", Research in Developmental Disabilities, Elsevier, Volume 111, April 2021, Pages 1-11. https://doi.org/10.1016/j.ridd.2021.103885

[11] Muhammad Shuaib Qureshi , Muhammad Bilal Qureshi , Junaid Asghar, Fatima Alam, and Ayman Aljarbouh, "Prediction and Analysis of Autism Spectrum Disorder Using Machine Learning Techniques", Journal of Healthcare Engineering, Hindawi, Volume 2023, July 2023, Pages 1-10. https://doi.org/10.1155/2023/4853800

[12] Mousumi Bala, Mohammad Hanif Ali, Md. Shahriare Satu, Khondokar Fida Hasan and Mohammad Ali Moni, "Efficient Machine Learning Models for Early-Stage Detection of Autism Spectrum Disorder", Algorithms, Volume 15, Issue 5, 2022, Pages 1-22. https://doi.org/10.3390/a15050166

[13] Fahima Hajjej, Sarra Ayouni, Manal Alhouhali, and Mohamed Maddeh, "Novel Framework for Autism Spectrum Disorder Identification and Tailored Education With Effective Data Mining and Ensemble Learning Techniques", IEEE Access, 2024, Pages 1-14. **DOI:** 10.1109/ACCESS.2024.3349988

[14] Martin Schulte-Ruther, Tomas Kulvicius, Sanna Stroth, Nicole Wolff, Veit Roessner, Peter B. Marschik, Inge Kamp-Becker and Luise Poustka, "Using machine learning to improve diagnostic assessment of ASD in the light of specific differential and co-occurring diagnoses", Journal of Child Psychology and Psychiatry, Volume 64, Issue 1, 2023, Pages 16–26. **https://doi.org/10.1111/jcpp.13650**

[15] Razieh Asgarnezhad, Karrar Ali Mohsin Alh am eedawi, Hani Akram Mahfoud, "An Effective Model Of Autism Spectrum Disorder Using Machine Learning", Indonesian Journal of Electrical Engineering and Informatics (IJEEI), Volume 11, Issue 2, June 2023, pp. 389~401. **DOI**: 10.52549/ijeei.v11i2.4060

[16] Tapotosh Ghosh, Md. Hasan Al Banna, Md. Sazzadur Rahman, M. Shamim Kaiser, Mufti Mahmud, A.S.M. Sanwar Hosen, Gi Hwan Cho, "Artificial intelligence and internet of things in screening and management of autism spectrum disorder", Sustainable Cities and Society, Elsevier, Volume 74, 2021, Pages 1-85, https://doi.org/10.1016/j.scs.2021.103189

[17] Mohemmed Sha,Abdullah Alqahtani, Abdullah Alqahtani, Shtwai Alsubai, and Ashit Kumar Dutta, "Modified Meta Heuristic BAT with ML Classifiers for Detection of Autism Spectrum Disorder", Biomolecules, Volume 14, Issue 1, 2024, Pages 1-28. https://doi.org/10.3390/biom14010048

[18] Shu Lih Oh, V. Jahmunah, N. Arunkumar, Enas W. Abdulhay, Raj Gururajan, Nahrizul Adib, Edward J. Ciaccio, Kang Hao Cheong, U. Rajendra Acharya, "A novel automated autism spectrum disorder detection system", Complex & Intelligent Systems, Springer, Volume 7, 2021, Pages 2399–2413. https://doi.org/10.1007/s40747-021-00408-8

[19]Muhammad Shoaib Farooq, Rabia Tehseen, Maidah Sabir & Zabihullah Atal, "Detection of autism spectrum disorder (ASD) in children and adults using machine learning", Scientific Reports, volume 13, 2023, Pages 1-13. https://doi.org/10.1038/s41598-023-35910-1

[20] Sule Yücelba, Cüneyt Yücelba, "Autism spectrum disorder detection using sequential minimal optimization-support vector machine hybrid classifier according to history of jaundice and family autism in children", Concurrency Computation Practice and Experience, Wiley, Volume 34, Issue 1, 2022, Pages 1-13. https://doi.org/10.1002/cpe.6498