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AUTISM SPECTRUM DISORDER DETECTION IN TODDLERS AND ADULTS USING DEEP LEARNING

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Autism spectrum disorder includes symptoms like anxiety, depressive disorders, and epilepsy because of its impact on relationships, learning, and employment. Since no confirmed treatment and diagnosis are available, the emphasis is on improving an individual's capacities through symptom mitigation. This work investigates autism screening for adults and toddlers utilizing deep learning. We investigated models for feature prediction and fused these predictions with the original dataset to be trained with deep long short-term memory (DLSTM). Features are fused from the training and testing sets and then combined with the original dataset. Data analysis is carried out to detect anomalies and outliers, and a label encoding technique is utilized to convert the categorical data into numerical values. We hyper-tuned the DLSTM model parameters to optimize and assess significant outcomes. Experimental analysis and results revealed that the proposed approach worked better than the other techniques, yielding 99.9% accuracy for toddlers and 99% for adults.

Keywords: autism spectrum disorder (ASD), deep learning, feature fusion, feature prediction, healthcare.

1. Introduction

Autism spectrum disorder (ASD) is frequently related to intellectual difficulties because its symptoms usually appear in the initial two years of existence (Reddy, 2024). Individuals with ASD can experience behavioral, cognitive, learning, and interpersonal challenges. Since there are so many different signs and variations in their severity, ASD is acknowledged as a spectrum

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disorder (Simeoli *et al.*, 2024). If the chronic illness is adequately addressed, productivity and symptoms can be improved. People with autism may exhibit irregular glances, struggle to understand individuals, have difficulties comprehending discussions, and have delayed or discordant facial reactions to words. They may find it challenging to adapt to social interactions. Experimental evidence indicates that a person's genes and circumstances can have a crucial role in the development of ASD, even though the precise etiology of the illness is uncertain (Ahmed *et al.*, 2022; Simeoli *et al.*, 2024; Atlam *et al.*, 2024). Additionally, it has been discovered that individuals with autism have a considerably reduced quantity of neurons in the cerebellum (Baizer, 2024).

The procedure of detecting ASD in toddlers typically involves two stages. During the first phase, infants are regularly evaluated for cognitive deficits. If ASD indicators are detected during a preliminary diagnostic procedure, more diagnostic testing could be carried out. This assessment could consist of hearing screenings, a neurological examination, an intellectual assessment, behavior observations, and linguistic assessments (Shrivastava *et al.*, 2024). Adults who are evaluated for sensory problems, repetitive behaviors, and communication difficulties may find the diagnosis to be a little difficult. Timely intervention is essential for assisting an individual with ASD in managing impulsivity, attention problems, depression, and stress. Adequate pharmaceuticals and therapy regimens can assist these people in developing language, social, and communication skills and reduce disruptive behaviors in their everyday lives. According to recent studies, the New York metropolitan region's autism rates among adolescents potentially tripled between 2000 and 2016 (Alqaysi *et al.*, 2022). One in forty-four toddlers received an ASD diagnosis in 2018 (Alsuliman and Al-Baity, 2022). Many studies have been done in previous decades to investigate autism in humans or to suggest possible treatments for the condition. Eye-gazing motions can give visual preference trends that help diagnose autism in people (Bala *et al.*, 2022). Physiological and sociodemographic characteristics might also be examined to diagnose autistic patients (Barik *et al.*, 2023).

The knowledge of the illness has also been enhanced by neuroscience research on white matter microstructural disintegration (Chaste and Leboyer, 2012). Similarly, many medical studies and methodologies have examined autism in human subjects (Francese and Yang, 2022; Kanhirakadavath and Chandran, 2022). Though earlier research has provided individual analysis through various techniques, a thorough examination of toddlers and adolescents in those studies has yet to be done. An effort has been put forth to create an effective and profitable way to recognize ASD patients with impressive ASD diagnosis precision and productivity. It was done using artificial intelligence (AI) (Shahamiri and Thabtah, 2020), and machine learning (ML) (Song and Ying, 2015; Hsu, 2003) techniques. The goal was to minimize all the drawbacks, such as the lengthier diagnosis times, higher costs, and the need for more personnel. Nevertheless, there is a lack of solid research to comprehensively examine the advantages and disadvantages of utilizing various parts of ML techniques to identify indicators associated with ASD accurately. The present research addressed several ML techniques for determining ASD to bridge this knowledge deficit. By addressing many facets of the application of ML approaches in diagnosing ASD patients through a supervised methodology, we attempted to close this discrepancy in our work. The model's efficiency was assessed using six ML techniques, including feature prediction and the LSTM model, each with a distinct set of performance indicators.

The specific contributions are as follows:

- This study proposes a hyper-tuned DLSTM model for ASD detection in toddlers and adults by fusing features provided by ML prediction models later with the original features matrix for efficient ASD detection.
- Data are preprocessed by analyzing and converting the categorical data into numerical values for feature prediction. The study uses several statistical measures to assess the performance of the ASD categorization model.
- Experimental analysis and results revealed that the proposed approach worked better than the other techniques, yielding 99.9% accuracy for toddlers and 99% for adults. The results indicate that this approach is efficient for ASD detection in toddlers and adults.

This paper is structured as follows. Section 2 presents the background and relevant works. The proposed approach for ML and DL models for ASD is introduced in Section 3. In Section 4, the performance of our technique is assessed and contrasted with the baseline methods. The paper is concluded, and future research is provided in Section 5.

2. Related work

ASD is caused by diseases including anxiety, depressive disorders, and epilepsy because of its impact on a person's social, academic, and professional components. Since there is no proven cure and identification is challenging, the goal is to maximize an individual's potential through symptom mitigation. Additionally, enhanced behavior and linguistic growth followed initial recognition (Shahamiri *et al.*, 2022; Beary *et al.*, 2020; Omar *et al.*, 2019). Raj and Masood (2020) investigated potential applications of ML and DL models for the study and prediction of ASD issues in toddlers, teens, and adults. Three distinct publicly accessible nonclinical ASD datasets are used to assess the proposed methodologies. Results strongly imply that CNN-based models for predicting perform more effectively with a better accuracy of 99.53%, 98.30%, and 96.88% for ASD inspection in data for adults, toddlers, and teenagers, respectively.

In the work of Farooq *et al*. (2023), the FL approach is utilized for the recognition of autism by learning two distinct machine learning classifiers, LR and SVM, for the identification of ASD in both toddlers and adults. Four distinct ASD clinical datasets, comprising over 600 data of impacted adults and children, were acquired from various repositories to derive variables. For children, the proposed model diagnosed ASD with an accuracy of approximately 98%, and for adults, an accuracy of 81%. The primary objective of Reddy (2024) is to employ a DL model to identify autism utilizing facial envision data. The authors accurately diagnosed autism in toddlers using DL models for feature extraction and binary classification algorithms. The proposed models were trained using a dataset of 3014 images of children categorized as autistic and nonautistic. The models yielded accuracy values of 87.9%, 80.05%, and 84.66%, respectively.

Lu and Perkowski (2021) presented a feasible method for ASD testing using face images, employing a VGG16 transfer learning approach. The proposed model produced a 95% accuracy at an F1-score of 95. Ahmed *et al*. (2022) used three AI methods for the early detection of autism: ML, DL, and a hybrid technique integrating the two. The first approach classifies characteristics using NNs: artificial neural networks (ANNs) and feedforward neural networks (FFNNs). A hybrid method is used to derive characteristics by combining the powers of the local binary pattern (LBP) and grey-level co-occurrence matrix (GLCM) methods. This technique was able to produce FFNNs and ANNs with an accuracy of 99.8%. The second method relied on deep feature map retrieval and employed a pre-trained CNN model, such as GoogleNet and ResNet-18. Exceptional outcomes of 93.6% and 97.6% were attained by the GoogleNet and ResNet-18 models, respectively. The third method, GoogleNet + SVM and ResNet-18 + SVM, combined ML and DL in a hybrid fashion. Wang *et al*. (2019) used a DL classifier in conjunction with innovative feature design and encoding approaches for testing ASDs. Combining a strong DL classifier and a deep embedding model for categorical data, strategies were developed for diagnosing ASD based on personal and behavioral traits. The recommended approach outperforms baselines, achieving 99% specificity and sensitivity. Ashok and Gopikrishnan (2023) used the Internet of medical things (IoMT) to integrate multiple healthcare devices to improve patient monitoring and real-time care operations. Casalino *et al*. (2023) considered acoustic features of speech to detect bipolar disorder. They investigated how semisupervised and supervised learning could be used for mental health monitoring.

Kanhirakadavath and Chandran (2022) tested the suitability of vision-tracking data in youngsters to support earlier autism detection using ML techniques. The study used graphical gaze tracking scan route images to predict autism by comparing the efficacy of several ML algorithms. The authors used a DNN classifier and three conventional ML models for their empirical tests. A publicly accessible dataset including 547 visual gaze tracking scan processes from 328 normally developing toddlers and 219 autistic children was used in this research. The DNN model achieved 91.38% specificity, 97% AUC, 90.06% PPV, 93.28% sensitivity, and 94.46% NPV, outperforming conventional ML techniques on the populated dataset. Mohanty *et al*. (2021) presented a novel method for utilizing a deep algorithm to identify ASD. The subsequent steps are used to identify ASD. By explaining ASD symptoms using feature evaluation, the assessment procedure becomes more efficient. Moreover, ML algorithms report the ASD class type and evaluation variables. This study aims to reduce the data density using principal component analysis (PCA) and classify the ASD category using DNN.

Garg *et al*. (2022) suggested a hybrid method that combines explainable artificial intelligence (XAI) with DL to detect the most important characteristics for accurate and timely ASD prognosis. The proposed framework provides suggestions for expected outcomes and improved predicting, which will be crucial therapeutic support for better and earlier predicting ASD features in toddlers. The proposed model yielded 98% accuracy. Deng *et al*. (2022) constructed a spatial-temporal transducer to diagnose ASD employing time series fMRI. The imbalance problem has been addressed using a Gaussian technique. Even though the overall accuracy attained is much less than that of current techniques, the study uses two different datasets to verify the robustness of the model. Transformers are complicated, expensive to compute, and take a long time to train.

In summary, extensive and varied datasets are necessary for training both ML and DL models to guarantee stable results across various ethnic and cultural contexts, as shown in Table 1. In addition, moral and comprehension issues need to be considered to guarantee the appropriate use of these methods for autism screening. To create efficient and morally acceptable screening instruments for autism spectrum disorder, doctors, researchers, and technologists must work together. In this study, we investigated six ML methods for feature prediction, and an LSTM model was used to test the model's efficacy. Each strategy was examined using a different set of performance indicators.

Table 1. Literature review summary.

Study	Method	Performance	Gap
Reddy (2024)	DL models	Accuracy = 87%	Low performance
Farooq *et al.* (2023)	FL	Accuracy = 81% for adults	Low performance
Lu and Perkowski (2021)	VGG16 model	Accuracy = 87%	Low performance
Raj and Masood (2020)	ML and DL models	Accuracy = 96.8%	No clinical validation is provided
Kanhirakadavath and Chandran (2022)	ML models	91% specificity	Low performance

3. Proposed methodology

This section explains the whole procedure of the proposed approach. The proposed method comprises multiple steps: obtaining datasets, preprocessing data, and making model predictions. Figure 1 visualizes the proposed architecture. The initial stage of the data processing pipeline transforms textual variables into numerical form using a label encoder so that ML algorithms can comprehend it. Then, to train and assess the models' effectiveness, the dataset is divided into training and test sets. An important part is selecting features that maintain model accuracy and complexity. Features from the training and test sets are then merged using ML algorithms. This merged feature set trains an LSTM model for sequential data. Ultimately, the LSTM model generates predictions that indicate an individual's probability of exhibiting traits indicative of autism.

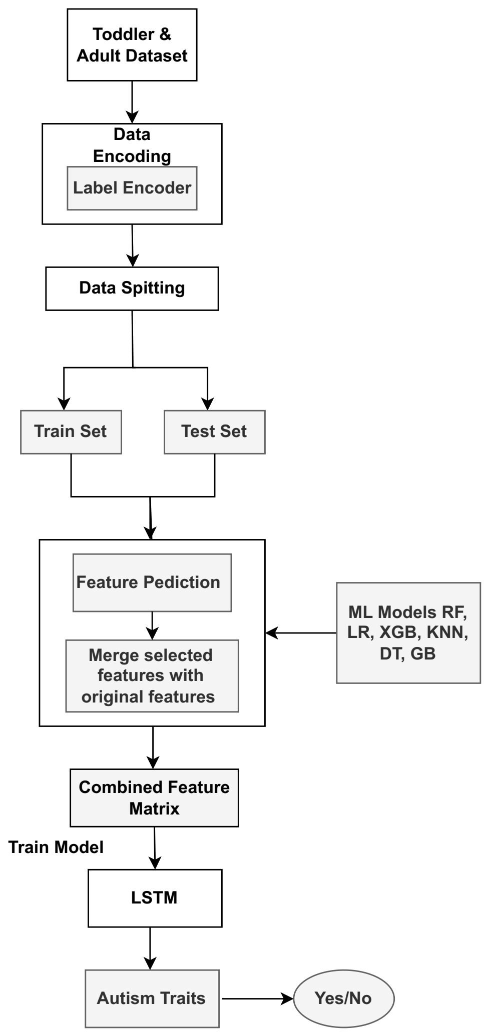


Fig. 1. Overview of the proposed architecture.

3.1. Dataset selection. This study aims to detect ASD in adults and toddlers using the LSTM model. The two distinct datasets used for the investigation regard the autism assessment for adults and toddlers and are obtained from Kaggle at `https://www.kaggle.com/datasets/andrewmvd/autism-screening-on-adults`. The toddler autism test data includes significant characteristics for determining tendencies toward autism. The dataset parameters consist of ten behavioral factors and additional features. Possible responses to queries like "Always," "Usually," "Sometimes," and "Never" are translated to values 1 and 0 because the parameters vary from A1 to A10. A user with qualities associated with ASD receives more than three points. The autism diagnostic dataset for adults contains 704 rows and 21 columns, while the dataset for toddlers has 1054 rows and 19 columns. Both databases share certain characteristics, such as gender, ethnic background, age, jaundice, etc. The proposed LSTM is implemented in both datasets to study ASD in toddlers and adults.

3.2. Data preprocessing. Data preprocessing is important in statistical analysis and ML to ensure reliability, effectiveness, and objective outcomes. It transforms unformatted data into comprehensible data. Cleaning, integrating, transforming, and validating data are crucial tasks. It is also essential to properly comprehend the data, document processes, and use specific tools to prepare it for analysis or modeling.

Encoding categorical variables. Categorical variables challenge certain ML techniques. The classification variable must be transformed into numerical data, which is crucial for the designed algorithms to function as intended. The different algorithms work according to the coding of the category variables. The dataset associated with a feature may have several labels in text or numerical form. This renders the data for humans easier to examine, but it is incomprehensible for machines (Sharma *et al.*, 2020). We utilize an encoding that renders these labels interpretable by machines. Other encoding methods include hash and one-hot encoding. This study encodes categorical data using the label encoding technique.

Label encoder. A numerical label input is made possible in an ML model using label encoding. A label encoder uses numbers to assign a value to each label, replacing the values of each label in the dataset. When they have divergent priorities, the labels can be employed. This step is crucial in the data preparation process for supervised learning methods (Sharma *et al.*, 2020). Usually, this technique replaces each value in a category column with a number between 0 and $N - 1$. In this study, a label encoder assigns a value of 0 to 1 or 2 to each categorical variable. This makes it possible to avoid overfitting and aids in determining how generalizable the predictions are. Initially, the dataset for toddlers and adults is split into two sets: 20% for testing and 80% for training. The training set size is determined as

$$N_{\text{train}} = \text{round}(N \times \text{train ratio}), \tag{1}$$

while the test set size is selected as

$$N_{\text{test}} = N - N_{\text{train}}. \tag{2}$$

3.3. ML-based feature prediction and fusion. Selecting a subset of pertinent features from an initial set of features to enhance model performance and minimize overfitting is known as feature prediction. The objective is to eliminate redundant or less contributing features, leaving just the most informative features for prediction. Feature prediction is essential to increase the predictive accuracy, decrease the computational challenge, and improve the model interpretability. This study utilized multiple ML models as feature prediction techniques, such as RF, LR, XGB, KNN, DT, and gradient boosting, to enhance the performance of the proposed LSTM model for autism toddlers and adult screening.

Random forest (RF). Numerous decision trees are combined using an ensemble learning technique called the random forest to create a more precise and reliable framework. It belongs to the class of tree-based models and is an extremely popular model for regression and classification applications (Al Duhayyim *et al.*, 2023). Using a random feature choice, random forest models build several decision trees independently, each trained on bootstrapped dataset samples. The model is less likely to overfit than individual trees because it aggregates predictions from individual trees by majority voting or averaging, which lowers variance and improves generalization performance (Mohammad *et al.*, 2022).

Logistic regression (LR). It is a fundamental classification approach used to model the probability of a binary outcome based on many predictor variables. The probability of a case falling into a particular class is calculated using a logistic function. Despite its name, it is a linear model that takes a linear combination of input features and assigns a logistic (or sigmoid) operator. Binary task classification benefits greatly from the interpretability, computational efficiency, and suitability of LR (Hosmer Jr *et al.*, 2013).

Extreme gradient boosting (XGB). It is a powerful ensemble learning method based on gradient boosting. Gradient descent is used to maximize the weak learners; usually, decision trees are constructed one after the other. Rapid processing on structured/tabular data, efficiency, and scalability are well-known attributes of XGBoost (Chen and Guestrin, 2016). It has built-in functionality for handling missing values and uses regularization techniques to avoid overfitting.

k-Nearest neighbors (KNN). It is an effective supervised training method for applications requiring classification. It finds the k-nearest observations from a particular query point in the training set to produce predictions. From there, it predicts its neighbors' average value (for regression) or a majority class (for classification) (Zhang and Zhou, 2005). Because kNN relies on retaining the entire training dataset, it can be extremely costly for massive amounts of data, despite its ease of use and comprehension.

Decision tree (DT). These are supervised learning algorithms that create regions in the feature area by making decisions based on the supplied characteristic values. The tree finds which attributes best separate the data at each node by optimizing a chosen criterion, such as data acquisition or Gini impurity. This process iterates back and forth unless an end condition is satisfied, such as reaching a maximum depth or a minimum amount of samples per leaf. Decision trees are widely used in many different sectors because of their ease of understanding and ability to handle numerical and categorical data.

Gradient boosting (GB). It constructs a sequence of weak learners, usually decision trees, sequentially. Fitting each new model to the negative gradient of the loss value, the ensemble's predictions reduce the loss function. By adding new models that fix mistakes caused by the older ones, gradient boosting iteratively enhances the model's performance. It is frequently utilized in machine learning contests and practical applications due to its strong predicted accuracy, resilience to overfitting, and capacity to manage intricate datasets.

3.4. Deep long short-term memory. The growing slope and disappearing problem can be resolved using memory blocks rather than standard recurrent neural network (RNN) units (Amin *et al.*, 2021). The main distinction between LSTM and RNN is that LSTM incorporates the cell state to preserve the long-term states. An LSTM network can retrieve and link previous data to present information (Chen, 2016). Three distinct gates are used in the architecture of long short-term memory: the input, forget, and output gates. The cell's new and prior states are designated by n_t and n_{t-1}, respectively, while the current and previous outputs are indicated by o_t and o_{t-1}, respectively. The current input is indicated by c_t.

The following equations provide the rules for the LSTM's input gate. In

$$L_t = \sigma(D_i \cdot [v_{t-1}, p_t] + g_i) \tag{3}$$

the input gate is represented by g_i, and the preceding outputs, v_{t-1} and p_t, are passed through the sigmoid layer for deciding which portion of the information needs to be added.

After transferring the old information, p_{t-1}, and the current information, c_t, by the $\tanh$ layer using the input gate a_i,

$$U_t = \tanh(D_i \cdot [p_{t-1}, c_t] + a_i) \tag{4}$$

is utilized to obtain the updated information U_t . Equation

$$C_t = h_t(S_{t-1}) + j_t s_t \tag{5}$$

integrates the information of long-term memory S_{t-1} into S_t and the present state of information C_t . The sigmoid output is denoted by D_i, while S_t means the $\tanh$ output. D_i represents the weight metrics, and a_i represents the LSTM's input gate. Using the dot product of the input information J_t and the current state of information s_t and sigmoid layer, the forget gate of the LSTM then enables the particular transmission of the data.

The probability of deleting the linked data by the final cell is given by

$$b_t = \sigma(D_f \cdot [p_{t-1}, u_t] + a_f). \tag{6}$$

The weight matrix is represented by D_f, the offset is a_f, and the sigmoid function is σ.

The inputs in

$$T_t = \sigma(D_o \cdot [o_{t-1}, p_t] + a_o), \tag{7}$$

$$F_t = T_t \tanh(N_t). \tag{8}$$

establish that the states required for the continuation through the previous and current outputs, o_{t-1} and p_t, respectively, are described by the output gate T_t of the LSTM. The decision vector of the condition that transmits new information N_t by the $\tanh$ layer is multiplied and acquired by the final output F_t. Here a_o denotes the bias of the LSTM of the output gate and D_o is its weighted matrix (Islam *et al.*, 2020).

The three gates in the framework are the output, forget, and input gates. The first gate, known as a forget gate (h_t), takes the current input, c_t, and the previous output, o_{t-1}, from the prior state, P_{t-1}, using a sigmoid function of σ. Once the previous data has been added, the input gate employs the $\tanh$ layer and the sigmoid function σ to receive input information J_t. The input gate provides the data, which are then fed into the output gate, which computes all the data and outputs the current state, where the output is retained, using the sigmoid function σ.

Algorithm 1. Pseudo code for autism detection on toddlers and adult data.

Input: $Autism\ Data$
Output: $Autism\ predicting$
function CreateandprepareAutismDataset():
  D_e = Data Encoding
  LE = label encoder
  DS = $X\_train, x\_test, , Y\_train, Y\_test$
function CreateMLModel:
  F_s = feature prediction (train and test set)
  $C_f s$ = Combined selected features
  return Return (x, y)
function ModelTrain(x, y):
  $LSTM$ = Create LSTM Model
return $model$
function ASDPrediction $(model)$:
  $E_m \leftarrow$ Evaluation metrics
Return (ASD Predictions)

Algorithm 1 uses a multi-step procedure to examine ASD using toddler and adult data. The framework provided enhances autism diagnosis in toddlers and adults more easily using ML techniques. It starts with data on autism as inputs and produces projections of traits linked to autism. An autism dataset is created, split into training and test sets, and processed with a label encoder as the initial data preprocessing stage. The *CreateMLModel* function then picks features and merges features from both sets. In the *ModelTrain* function, an LSTM model is then trained using the combined feature vectors. Finally, the *ASDPrediction* function uses metrics to assess the training model and returns predictions on ASD features (Yes/No). The method synchronizes operations, such as data preparation, model development, training, and prediction, to determine autism symptoms from the data input.

4. Results and discussion

This section provides extensive details on how the toddler and adult dataset is used to identify autism using the DL model. 20% of the dataset is used for testing and

80% for training. This model makes learning from the provided dataset easier by using the characteristics of the DL classifier. Moreover, statistical measures are used to assess the efficacy of this strategy. This part summarizes and evaluates the test findings and provides an in-depth, insightful data analysis. This study assesses the framework's efficacy using extensive evaluation criteria, each offering valuable perspectives on the model's operation. The first metric, accuracy, is typically used as the standard to evaluate performance. It is computed as the part of accurately recognized samples based on the total sample amount.

Accuracy is the ratio of all positive predictions the model produces to effectively precise projections,

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{9}$$

It is a crucial assessment metric utilized in performance evaluation.

Precision indicates how the model predicts the positive class,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{10}$$

It represents the accuracy of the model and the degree of confidence in its ability to produce good predictions. This value is shown proportionately in Equation 10, facilitating comprehension of the metric basic equation.

Recall, also called sensitivity, is an evaluation metric that centers on the ratio of every positive instance to the percentage of precise positive predictions. It is defined as

$$\text{Recall} = \frac{\text{TP}}{\text{TN} + \text{FN}}. \tag{11}$$

The appropriately identified F1 score functions as an equilibrium of recall and precision because it can effectively communicate the essence of a balanced performance. Combining these two metrics yields the F1-score, a popular estimate of model performance that is especially useful for evaluation,

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{12}$$

One significant and unique indicator used in the evaluation process is the confusion matrix (CM), which is carefully designed to provide precise data regarding the efficacy of the classification model. This essential tool illustrates the model's efficacy by comparing the anticipated and actual data. The matrix section labels, which show the actual class designations, correspond to the columns. The correctly recognized samples are arranged along the diagonal, while the incorrectly categorized cases are situated on the diagonal portions. The CM values are an essential tool for assessment that can highlight the advantages and disadvantages of the model. They also provide insightful data that improves the model and produces favorable outcomes.

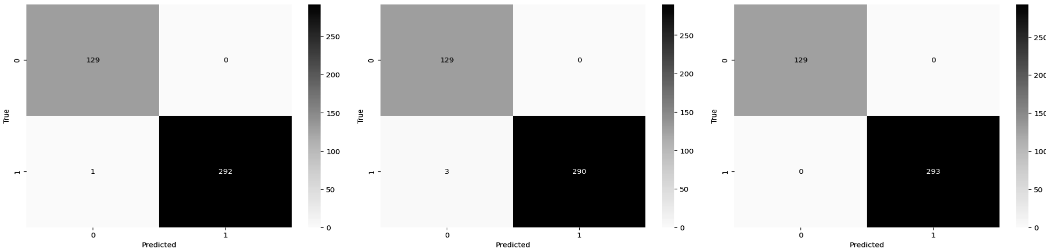
Table 2. DLSTM model results on different machine learning-based feature prediction techniques. FP: feature prediction.

Models	Accuracy	Recall	F1-score
RF based FP + LSTM	99	99	991
LR based FP + LSTM	99	98	99
XGB based FP + LSTM	100	99.9	99.9
KNN based FP + LSTM	97	95	97
DT based FP + LSTM	98	97	98
GB based FP + LSTM	96	95	97

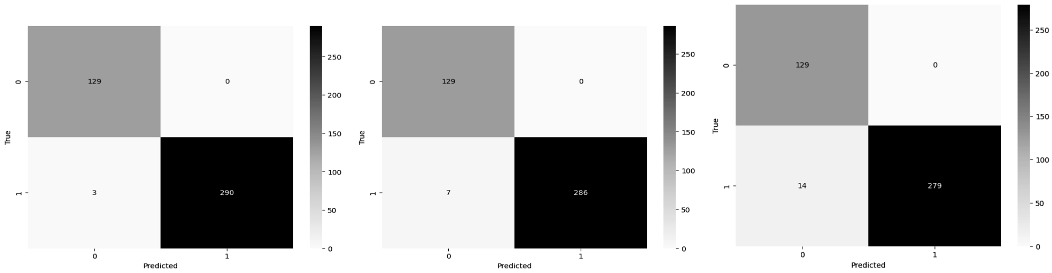
4.1. Results for the toddler autism dataset. The outcomes of an LSTM model using several ML-based feature prediction methods are displayed in Table 2 for autism detection in toddlers. The XGB classifier performed exceptionally well overall, achieving a score of 99.9% for all optimizing parameters. As a result, the XGB successfully classified every data point. The RF and LR techniques also yielded positive results, with an accuracy score of 99%. The KNN, DT, and GB models were nevertheless able to correctly categorize a significant amount of the data, although having slightly lower accuracy ratings. This demonstrates that ML-based feature prediction approaches might improve the overall performance of LSTM models. The XGB method was the most effective in this case, although RF and LR might also function well as feature prediction models.

Figure 2 represented the CM of an LSTM model using several ML-based feature prediction methods. The findings of an algorithm used to divide observations into two classes are displayed in the CM. The classes that the method anticipated are represented in each matrix column, while the actual classes of the information points are represented in the rows. Figure 2(a) demonstrates that the anticipated proportions are represented by the Class labels 0 and 1. For class 0, 129 instances were projected correctly, and 292 were diagnosed accurately for Class 1. Figure 2(b) represents the anticipated proportions for Classes 0 and 1. 129 instances were projected correctly, and 290 for Class 1 were detected accurately. Similarly, Figure 2(c) represents the XGB classifier CM; for Class 0, 129 autism cases are predicted accurately, while 293 autism cases are diagnosed correctly for Class 1. Figure 2(d) indicates the CM of the KNN model. For Classes 0 and 1, 129 and 290 autism cases are diagnosed accurately. Figures 2(a) and (f) demonstrate the CM of DT and GB. For Classes 0 and 1, 129 and 286 cases are predicted correctly for DT, and 129 and 279 autism cases are diagnosed for Classes 0 and 1, respectively, for GB.

Figure 3 represented the receiver operating characteristic (ROC-AU C) curves of an LSTM model using several ML-based feature prediction methods on

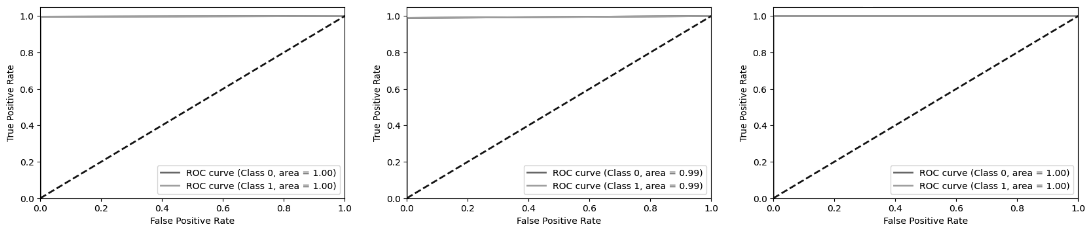


(a) RF-FP + LSTM -CM (b) LR-FP + LSTM -CM (c) XGB-FP + LSTM -CM

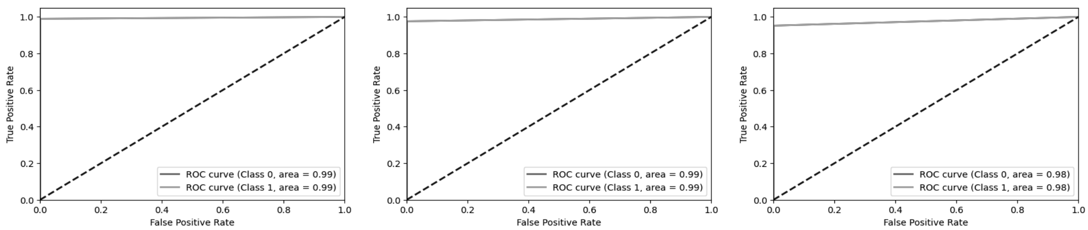


(d) KNN-FP + LSTM -CM (e) DT-FP + LSTM-CM (f) GB-FP + LSTM -CM

Fig. 2. Results for the toddler dataset: LSTM CM based on RF prediction (a), CM of LSTM based on LR feature prediction (b), confusion matrix LSTM based on XGB prediction (c), LSTM CM on KNN based prediction (d), DT based prediction of LSTM CM (e), LSTM CM based on GB feature prediction of toddler screening dataset (f).



(a) RF-FP + LSTM-ROC AUC (b) LR-FP + LSTM-ROC AUC (c) XGB-FP + LSTM-ROC AUC



(d) KNN-FP + LSTM-ROC AUC (e) DT-FP + LSTM-ROC AUC (f) GB-FP + LSTM-ROC AUC

Fig. 3. ROC-AUC curves on the toddler screening dataset.

the toddler autism screening dataset. The percentage of negative instances mistakenly categorized as positive is known as the false positive rate (FPR), and the x-axis on each ROC curve represents it. The true positive rate (TPR) is represented on the y-axis as the percentage of positive instances is accurately categorized as positive. The FPR and TPR conflict for various categorization criteria is displayed on the ROC curve.

Figure 4 shows the accuracy curves of many ML models on the toddler screening dataset. Based on the graphs, models such as RF and more trees assist them in understanding complex patterns in the data, which improves accuracy. The accuracy stability of RF, even when there are fewer trees, shows how effective it is at quickly identifying important patterns in data. GB and XGBoost systems increase accuracy as the number of trees increases, suggesting that they may comprehend intricate data patterns; however, overfitting is possible. On the other hand, compared with other models, classifiers such as LR, DT, and KNN exhibit poorer accuracy, indicating that they have difficulty learning complex data structures.

Figure 5 shows the loss curves of the LSTM model based on ML feature prediction techniques on the toddler screening dataset. Since more trees can detect more complex data structures, models with more trees have lower losses. RF maintains a steady loss even with fewer trees, demonstrating its quick learning of significant data structures. With more trees, both GB and XGBoost continue to increase their loss performance, indicating that they can understand increasingly more complicated patterns, though there is a chance of overfitting. In contrast, classifiers with lower losses, such as DT, KNNs, and LR, suggest that these models have a harder time understanding complicated data patterns than others.

4.2. Results for the adults autism dataset. The outcomes of an LSTM model using several ML-based feature prediction methods using an adult autism screening dataset are displayed in Table 3. It demonstrates that every feature prediction strategy attained high accuracy, obtaining a success rate of at least 96. An impeccable precision score of 1.00 was attained with RF, LR, DT, and GB. This indicates that all of the affirmative cases were appropriately detected. 98% of the positive results were accurately identified by XGB, with a precision of 98. With a precision of 98, the lowest of all, KNN correctly detected 98% of the positive outcomes. With a recall rating of 98, DT and GB were the most accurate in identifying 98% of the positive real instances. With a recall of 97, RF, LR, and XGB accurately classified 97% of the real positive cases. With a recall of 92, the lowest of all the networks, KNN accurately detected 92% of the real positive results. With an optimal F1-score of 99, DT demonstrated a good balance between recall and precision. With an F1-score of 98, RF, LR, and XGB demonstrated a good balance between precision and recall. With its F1-score of 95, KNN performed the least well among the approaches in balancing precision and recall.

Figure 6 represented the CM of an LSTM model using several ML-based feature prediction methods on the adult autism screening dataset. Figure 6(a) demonstrates that the class represents the anticipated proportions labels 0 and 1 for RF. For Class 0, 201 instances were projected correctly, and 79 were diagnosed accurately for Class 1. Figure 6(b) represents the anticipated proportions for LR classes 0 and 1. 201 instances were projected correctly, and 78 for Class 1 were detected accurately. Similarly,

Table 3. LSTM model results on different machine learning-based prediction techniques. FP: feature prediction.

Models	Accuracy	Recall	F1-score
RF based FP + LSTM	99	97	98
LR based FP + LSTM	98	96	98
XGB based FP + LSTM	99	98	98
KNN based FP + LSTM	97	92	95
DT based FP + LSTM	99	98	99
GB based FP + LSTM	96	85	92

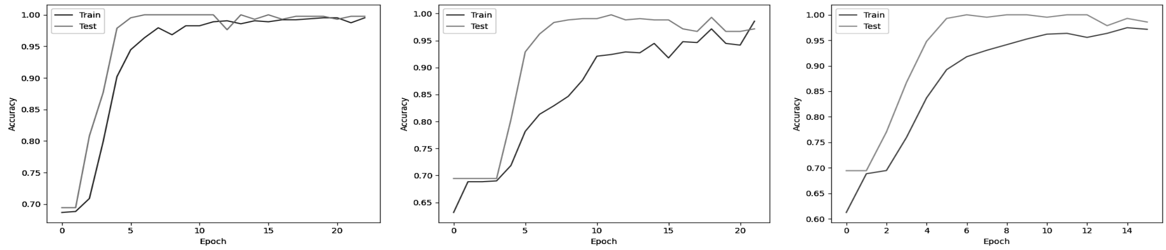
Fig. 6(b) represents the XGB classifier CM; for Class 0, 200 autism cases are predicted accurately, while 80 autism cases are diagnosed correctly for Class 1. Figure 6(d) indicates the CM of the KNN model. For Classes 0 and 1, 154 and 53 autism cases are diagnosed accurately. Figures 6(a) and (f) demonstrate the CM of DT and GB, respectively. For Classes 0 and 1, 155 and 56 cases are predicted correctly for DT, and 155 and 49 autism cases are diagnosed for Classes 0 and 1, respectively, for GB.

Figure 7 represented the receiver operating characteristic (ROC-AU C) curves of an LSTM model using several ML-based feature prediction methods (RF, LR, XGB, KNN, DT and GB) on the adult autism screening dataset.

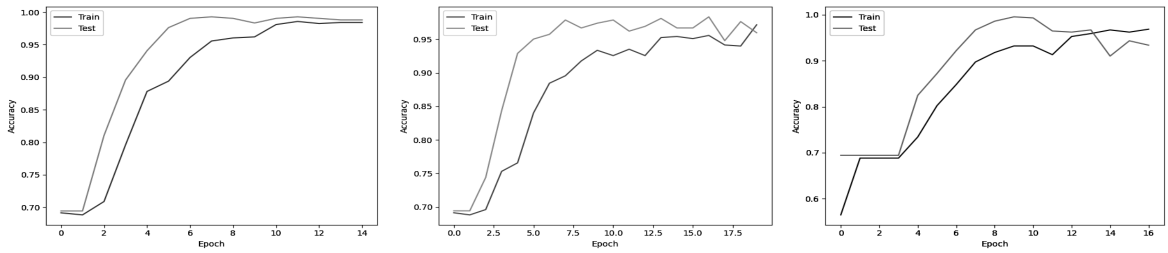
Figure 8 shows the accuracy graphs of ML techniques on the adult screening dataset. Test and training statistics indicate that the RF model is the most accurate, demonstrating strong learning without overfitting. On the other hand, the LR model learned poorly, as it had the lowest accuracy across both sets. Although the DT model overfits the training sample but performs average on the test data, the XGB Classifier model exhibits significant training accuracy but poor test accuracy, indicating overfitting. Finally, the GB model performs well on both datasets, suggesting effective training and avoiding overfitting.

Figure 9 shows the loss curves of ML models on the adult screening dataset. The loss curve of RF is linear and continuously dropping, demonstrating effective training and minimal overfitting. The straight but less steep curve for LR suggests that it might not be as effective. The curve of the XGB shows a tendency toward overfitting; it is similar to the RF curve but has some minor oscillations. The GB curve, comparable to that of RF but with larger variations, indicates effective training with a greater danger of overfitting. In contrast, KNN and DT tense curves reflect inferior learning.

4.3. Comparative analysis and discussion. Table 4 compared the proposed approach with existing techniques (Reddy, 2024; Rasul *et al.*, 2024; Lu and Perkowski, 2021). The study by Reddy (2024) has an

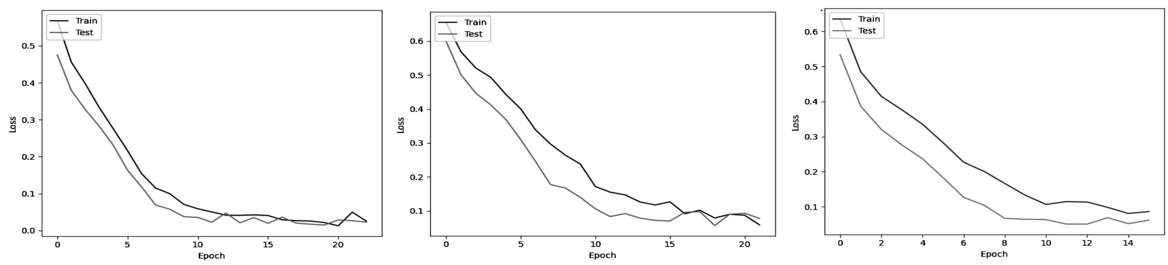


(a) RF-FP + LSTM-accuracy curve (b) LR-FP + LSTM-accuracy curve (c) XGB-FP + LSTM-accuracy curve

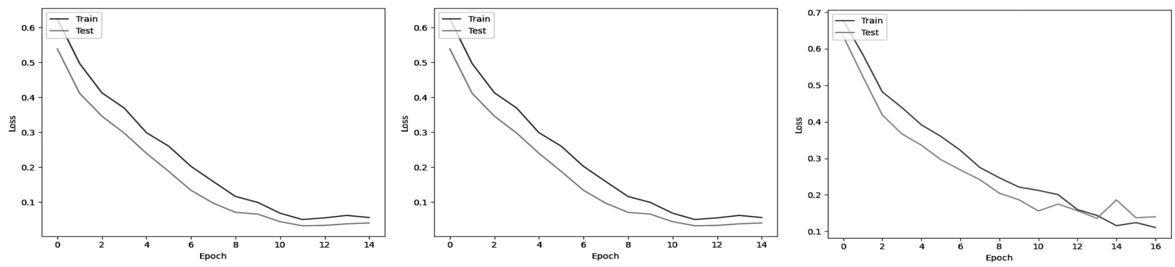


(d) KNN-FP + LSTM-accuracy curve (e) DT-FP + LSTM-accuracy curve (f) GB-FP + LSTM-accuracy curve

Fig. 4. Train and test accuracy curves on the toddler screening dataset.



(a) RF-FP + LSTM-loss curve (b) LR-FP + LSTM-loss curve (c) XGB-FP + LSTM-loss curve

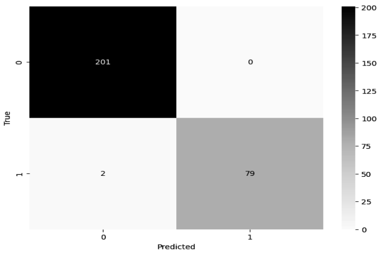


(d) KNN-FP + LSTM-loss curve (e) DT-FP + LSTM-loss curve (f) GB-FP + LSTM-loss curve

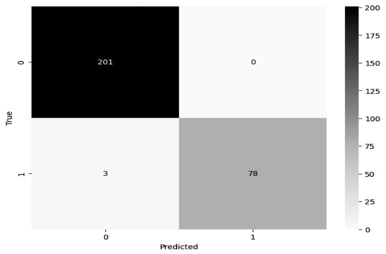
Fig. 5. LSTM train and test loss curves on the toddler screening dataset.

accuracy of 88.33% on the toddler ASD dataset, and that by Rasul *et al*. (2024) has 98.85% accuracy on the toddler dataset. In contrast, Lu and Perkowski (2021) report 96.67% accuracy for the adult dataset and 95% on the toddler dataset, whereas the proposed method achieved 100% for the toddler dataset and 99.0% for an adult dataset. The proposed technique performs better in this context than the base paper, indicating that our technique is superior in ASD detection.

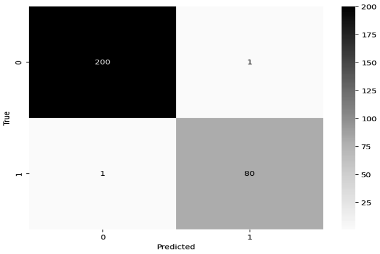
This study utilized the toddler and adult ASD datasets for autism diagnosis using different ML models for feature prediction. Issues with data quality hinder the development of ML models for autism screening because it is hard to find varied and well-annotated datasets.



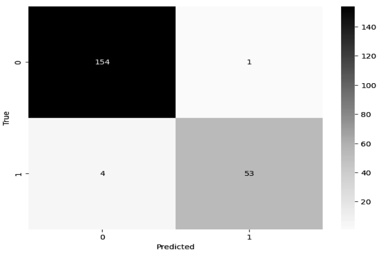
(a) RF-based FP +LSTM-CM



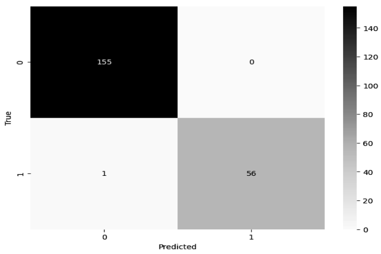
(b) LR-based FP + LSTM-CM



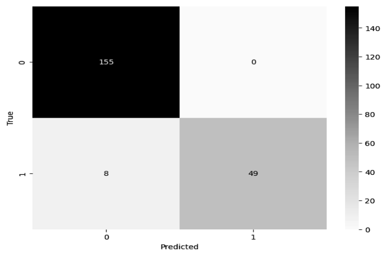
(c) XGB-based FP + LSTM-CM



(d) KNN-based FP + LSTM-CM

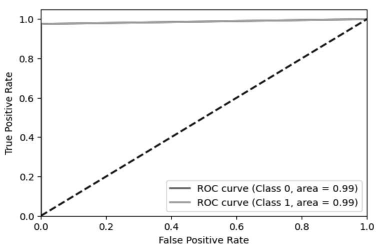


(e) DT-based FP + LSTM-CM

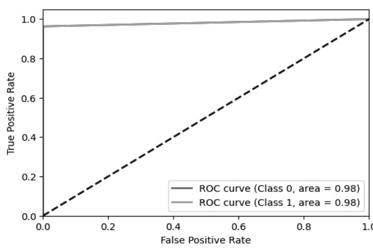


(f) GB-based FP + LSTM-CM

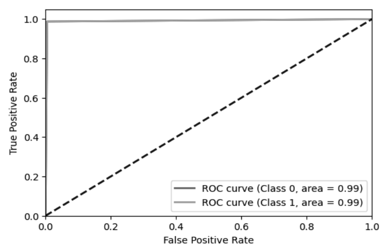
Fig. 6. Confusion metrics on the adult dataset.



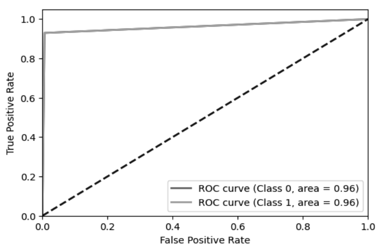
(a) RF-based FP + LSTM-ROC AUC



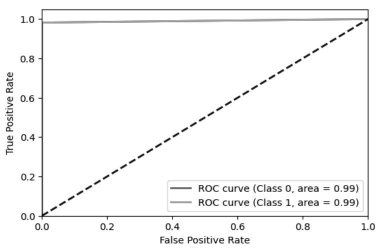
(b) LR-based FP + LSTM-ROC AUC



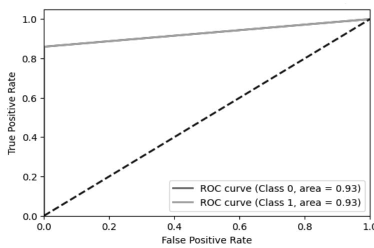
(c) XGB-based FP + LSTM-ROC AUC



(d) KNN-based FP + LSTM-ROC AUC



(e) DT-based FP + LSTM-ROC AUC

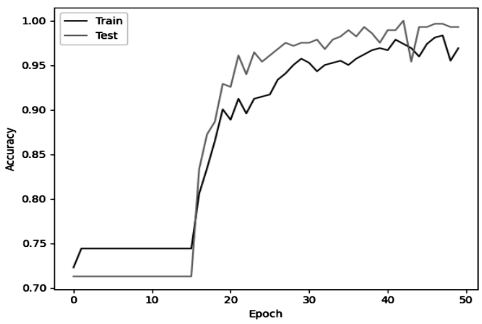


(f) GB-based FP + LSTM-ROC AUC

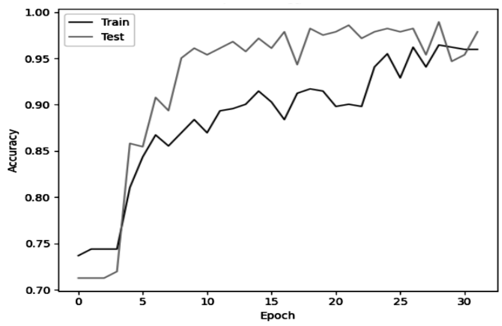
Fig. 7. ROC-AUC curve on the adult screening dataset.

Accurate data labeling is arbitrary and time-consuming; it necessitates professional diagnosis and multidisciplinary reviews, which adds to the process complexity. To guarantee efficient absorption, accessibility, and efficacy, engineers, doctors, and stakeholders must collaborate to integrate ML techniques into clinical processes. Clinicians need further training to evaluate and interpret algorithmic findings within the larger diagnostic process. This highlights the significance of interdisciplinary methods in healthcare technology.

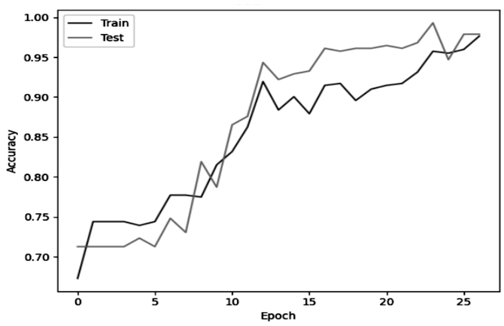
This study focuses on the feature fusion method for enhancing the performance of the proposed LSTM model. Machine learning models (RFLR, XGB, KNN, DT and GB) for feature fusion provide a strong and adaptable



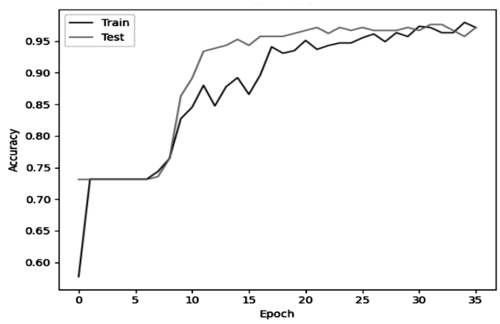
(a) RF-based FP + LSTM-accuracy curve



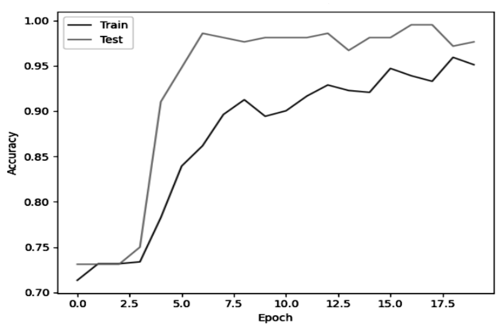
(b) LR-based FP + LSTM-accuracy curve



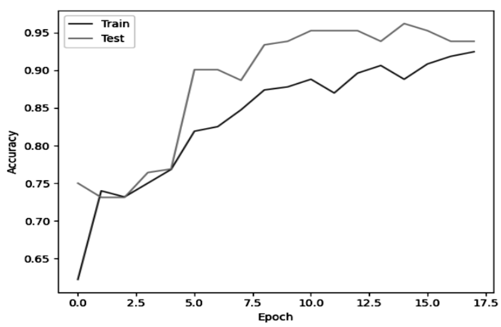
(c) XGB-based FP + LSTM-accuracy curve



(d) KNN-based FP + LSTM-accuracy curve



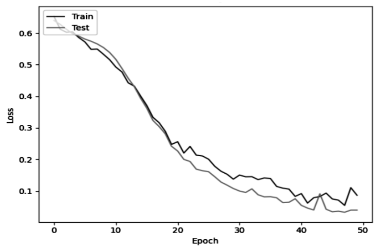
(e) DT-based FP + LSTM-accuracy curve



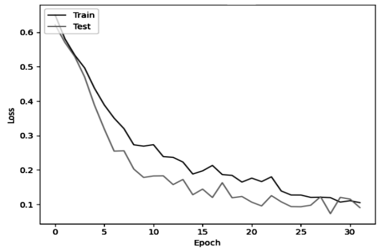
(f) GB-based FP + LSTM-accuracy curve

Fig. 8. Train and test accuracy on the adult screening dataset.

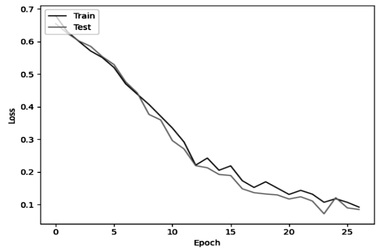
framework for combining data from several modalities or sources (training and testing set) to enhance performance. Features are fused from the training and testing sets (feature prediction), and these predicted features are combined with the original dataset features and generate a new combined feature matrix. The study demonstrates the exceptional effectiveness of the proposed LSTM model on the autism dataset, assessing its efficacy using optimization indicators essential for statistical analysis. The effectiveness, standardization potential, and relevance of DL models are examined through statistical analysis. Architectural features and parameter counts impact model complexity and are essential for identifying patterns and correlations in data. In complex models, regularization must be done correctly to reduce overfitting. To ensure that model performance stays robust, strategies such as regularizing the loss function and introducing penalty components can minimize intricacy while preventing overfitting. The study uses the LSTM model with six different ML models as feature prediction to tackle ASD issues. The experiment results indicate that the proposed LSTM architecture functions more accurately and efficiently than conventional DL techniques for detecting ASD.



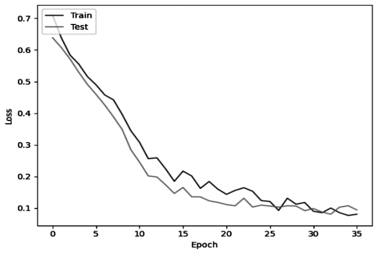
(a) RF-based FP + LSTM-loss curve



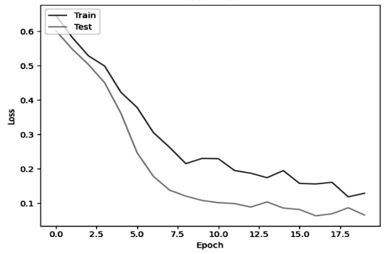
(b) LR-based FP + LSTM-loss curve



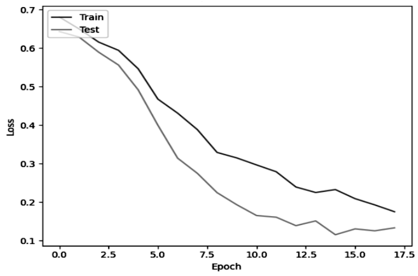
(c) XGB-based FP + LSTM-loss curve



(d) KNN-based FP + LSTM-loss curve



(e) DT-based FP + LSTM-loss curve



(f) GB-based FP + LSTM-loss curve

Fig. 9. LSTM train and test loss curve on the adult screening dataset.

Table 4. Comparison of the proposed model with the existing studies.

Model	Accuracy (toddlers)	Accuracy (adult)
EfficientBO	88.33%	NA
ANN	98.85%	96.67%
VGG16	95%	NA
Proposed model	99.9%	99.0%

5. Conclusion

Autism monitoring and detection is the procedure of identifying individuals at risk for ASD based on specific behaviors, developmental structures, and other traits. Using appropriate algorithms to evaluate various data sources, AI has demonstrated high potential for autism screening and diagnosis. To identify ASD in adults and toddlers, this study used ML techniques for feature prediction, and the LSTM model was trained. As part of the analysis, data visualization is done to find patterns in the data, and then ML models are used to conduct a thorough investigation. Two datasets were used to evaluate six ML frameworks, and several statistical parameters were used to assess the model effectiveness. Furthermore, several AI techniques have been offered to eliminate bias from the algorithm.

For the toddler dataset, the LSTM model performs better with the XGB classifier as the feature predictor, yielding 100% accuracy. In contrast, for the adult ASD dataset, RF, XGB, and DT perform better as feature predictors. It is found that the proposed study advances the previous studies based on empirical and comparative analyses. In the future, we want to use larger datasets and selfsupervised learning for the classification and learning of important patterns. Furthermore, we want to expand on our work by applying DL models that can simultaneously learn features, categorization, and clustering measures.

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