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Research Article

Unlocking the Potential of Autism Detection: Integrating Traditional Feature Selection and Machine Learning Techniques

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Abstract

The diagnostic process for Autism Spectrum Disorder (ASD) typically involves time-consuming assessments conducted by specialized physicians. To improve the efficiency of ASD screening, intelligent solutions based on machine learning have been proposed in the literature. However, many existing ML models lack the incorporation of medical tests and demographic features, which could potentially enhance their detection capabilities by considering affected features through traditional feature selection approaches. This study aims to address the aforementioned limitation by utilizing a real dataset containing 45 features and 983 patients. To achieve this goal, a two-phase methodology is employed. The first phase involves data preparation, including handling missing data through model-based imputation, normalizing the dataset using the Min-Max method, and selecting relevant features using traditional feature selection approaches based on affected features. In the second phase, seven ML classification techniques recommended by the literature, including Decision Trees (DT), Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), AdaBoost, Gradient Boosting (GB), and Neural Network (NN), are utilized to develop ML models. These models are then trained and tested on the prepared dataset to evaluate their performance in detecting ASD. The performance of the ML models is assessed using various metrics, such as Accuracy, Recall, Precision, F1-score, AUC, Train time, and Test time. These metrics provide insights into the models' overall accuracy, sensitivity, specificity, and the trade-off between true positive and false positive rates. The results of the study highlight the effectiveness of utilizing traditional feature selection approaches based on affected features. Specifically, the GB model outperforms the other models with an accuracy of 87%, Recall of 87%, Precision of 86%, F1-score of 86%, AUC of 95%, Train time of 21.890, and Test time of 0.173. Additionally, a benchmarking analysis against five other studies reveals that the proposed methodology achieves a perfect score across three key areas. By considering affected features through traditional feature selection approaches, the developed ML models demonstrate improved performance and have the potential to enhance ASD screening and diagnosis processes.

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1. Introduction

A complicated collection of neurological developmental illnesses known as autism spectrum disorder (ASD) also includes Asperger's syndrome, childhood disintegrative disorder, and an unspecified type of pervasive developmental disorder [1]. The extent and intensity of ASD symptoms can be quite broad, although they frequently include issues with social interaction and communication, obsessions, lack of eye contact, and limited or repetitive activities. Most often within the first five years of life, ASDs often manifest in early infancy and last throughout a person's lifespan [2]. The World Health Organization (WHO) estimates that one in 160 children worldwide has an ASD diagnosis [3]. From one in 100 to about one in 70 people, the prevalence of autism has grown by almost 40% in Australia [4]. One in 54 children in the United States had an ASD diagnosis in 2020, according to the Centers for Disease Control and Prevention (CDC) [5]. ASDs can significantly limit a person's capacity for engaging in social interaction and doing daily tasks. An individual's capacity to engage in social movements and carry out daily tasks is substantially impacted by ASDs. They frequently have detrimental impacts on social and academic success, career prospects, and the capacity to carry out everyday tasks and take part in society. People with ASD regularly experience abuse, discrimination, and human rights breaches on a global scale [6]. While there is presently no treatment for ASD, early intervention can help learning, communication, and social skills as well as brain development. Consequently, a method that is effective, efficient, and highly accurate is required for the diagnosis of ASD [2][7].
Autism can present in a wide range of symptom combinations, from mild to severe. It can hinder a kid's ability to engage and communicate with others, induce repeated behaviors and motions, make a child anxious when their daily pattern changes, and cause them to react in strange ways in specific circumstances [8]. Early indications of autism, such as a lack of babbling or pointing, can sometimes be seen in children as young as 12 months old. While specialists can occasionally diagnose and identify ASD at 18 months or earlier, it is frequently detected around the age of two, which is regarded as a very reliable age. Nevertheless, many kids don't get a definitive diagnosis until much later in life, like adolescence or adulthood. Children with ASD may not get the early help they require due to the diagnosis's delay. Autism diagnosis is also a time-consuming and expensive process. Each person with autism has distinctive traits, and they may have different assistance needs. Despite significant study, the root causes of ASD are still mostly unclear [9].
Furthermore, during the past 30 years, the reported prevalence of ASD has increased 20-fold, which is mostly attributable to the present diagnosis procedures [10]. Consequently, the detection of ASD can be a challenging task due to the absence of available medical tests for diagnosing the disorder. Screening tests to detect autism traits are often expensive and time-consuming. In this context, autism is more closely associated with medical and demographic characteristics than with genetic or environmental factors. Medical and demographic factors have received more attention in the detection and diagnosis of ASD [11][12]. Physicians often focus on these factors, hoping to identify strengths and detect correlations and relationships with ASD problems to aid in confirming the diagnosis [13]. Figure 1 illustrates the symptoms, comorbidities, and biomarkers associated with autism.

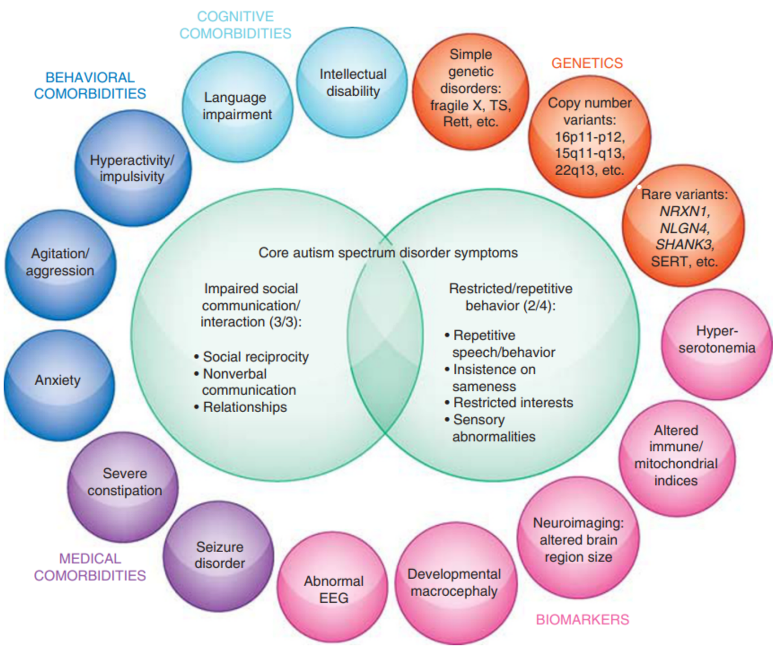

Figure 1 Autism symptoms, comorbidities and biomarkers [14]

Early diagnosis plays a crucial role in helping a child achieve important developmental milestones [15]. Thanks to the development of AI methodologies and other machine learning (ML) technologies, significant improvements in the

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detection of brain illnesses, including ASD, have been made [13]. ASD is a developmental disease marked by difficulties with social skills, repetitive habits, and verbal and nonverbal communication. ASD is often diagnosed in a clinical setting by qualified professionals utilizing techniques that may be time-consuming and inefficient [16]. In order to help in the diagnosis of autism and other pervasive developmental disorders, researchers in the disciplines of medicine, psychology, and applied behavioral science have created screening tools including the Autism Spectrum Quotient and Modified Checklist for Autism in Toddlers [16]–[18]. ML provides sophisticated methods for creating automated classifiers that can dramatically increase diagnostic discovery's sensitivity, specificity, accuracy, and effectiveness [19][20]. By 2025, it is anticipated that 90% of hospitals in the United States would be using medical AI, creating a $10 billion business [21], and potentially replacing up to 80% of current medical practices [22]. This revolution is based on the premise that AI can perform with expert-level accuracy and deliver cost-effective healthcare at scale [23]–[25]. Recent years have seen a significant increase in the application of AI in ASD research to speed up and streamline the diagnosing procedure as well as offer earlier access to treatments [26][27]. As a result, ML has promise as a tool for ongoing clinical and research work into ASD, offering prospective directions for enhancing ASD screening, diagnostic techniques, and therapy tools [28]. The financial burden of autism highlights the urgent need for the creation of simple, practical, and efficient early detection techniques [29].

Recent studies on detecting autism using ML have focused on assigning weights to ASD features constructed by physicians and applying these weights to the ASD dataset [30]–[32] However, this study adopts a different approach, focusing on traditional feature selection methods rather than constructing an ML model based on weighted features or the intersection of different ML methods and feature selection approaches. Several reasons justify this approach. First, Traditional feature selection methods are widely used and well-established techniques in machine learning. They offer a straightforward and interpretable way to identify the most relevant features for a given problem. By selecting a subset of informative features, the model's complexity can be reduced, enhancing its performance and interpretability. Second, Constructing an ML model based on weighted features or the intersection of different ML methods and feature selection approaches can be computationally expensive and may require additional resources and expertise. Traditional feature selection methods provide a simpler and more accessible approach, particularly for studies with limited resources or time constraints. Third, Traditional feature selection methods can provide valuable insights into the importance and relevance of specific features in the context of the problem at hand. By identifying the most influential features, researchers and practitioners can gain a deeper understanding of the underlying factors contributing to the prediction or classification task.

Furthermore, this approach was developed with the goal of creating a practical and applicable solution. Traditional feature selection methods strike a balance between simplicity and effectiveness, making them suitable for real-world applications where interpretability and ease of implementation are essential. This study focuses on traditional feature selection methods to further improve the model's performance and incorporate sophisticated feature selection strategies. The goal of this study is to build an ML model for detecting autism based on demographic and medical test data using ML algorithms and a traditional feature selection approach.

2. Literature Review

The field of medicine has witnessed the emergence of AI as an interactive tool with tremendous potential, particularly in the domains of diagnosis and decision-making support for healthcare professionals. ML algorithms have proven their ability to process vast and complex clinical data, making them a valuable asset in this revolutionizing development. The combination of AI and ML has transformative implications for healthcare on a global scale. Within ML, there exist diverse models that may produce slightly different outcomes when applied to ASD.

K. S. Oma et al. [33], proposed an ML-based prediction model and developed a mobile application for effectively predicting ASD in individuals of all age groups. This advancement holds promise for early detection and intervention. F. Thabtah et al. [34], introduced a novel ML method called Rules-ML, which not only detects autistic traits in cases and controls but also provides knowledge bases (rules) that aid domain experts in comprehending the underlying reasons behind the classification. This approach not only contributes to accurate classification but also enhances the interpretability of the results. S. Raj et al. [35], evaluated different techniques using publicly available non-clinical ASD datasets. This evaluation serves to advance research in the field by benchmarking the performance of ML algorithms and identifying areas for improvement. K. Akyol, [36], focused on identifying the essential attributes that contribute to the optimal detection of ASD across different age groups, including children, adolescents, and adults. Understanding these attributes can facilitate the development of more effective diagnostic tools. W. Liu et al., [29], explored the potential of ML algorithms in classifying children with ASD based on their face scanning patterns. This research offers insights into non-invasive and objective methods for diagnosing ASD, potentially improving early detection. M. D. Hossain et al., [37], aimed to identify the most significant traits associated with ASD and automated the diagnosis process using classification techniques. This automated approach can enhance the accuracy and efficiency of ASD diagnosis, reducing the burden on healthcare professionals. M. Garbulowski et al., [38], investigated gene expression measurements in individuals with ASD through case-control studies. They constructed a rule-based learning model using multiple datasets and visualized the results as a nonlinear gene-gene co-predictive network. This analysis provides insights into the genetic

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factors and interactions involved in ASD. To provide further analysis and information about the related literature, Table 1 presents a detailed description of the studies, including their authors, publication years, and key contributions.

Table 1 Description of literature review information

REF	Dataset size and availability	Methods types and	Metrics	Results	Normalization	Processing	Feature selection	Real-time detection
[33]	Three different datasets groups of child, adolescent and adult. AQ-10	Random Forest-CART and Random Forest-ID3	Accuracy Specificity Sensitivity Precision, FPR	AC=77%child,79 %Adolescent,85 %adult	✓	✓	✓	✓
[34]	Three methods were used using the AQ-10 child, adolescent, and adult data sets.	RIPPER, RIDOR, Nnge, Bagging, CART, C4.5, and PRISM	Sensitivity, specificity, accuracy	C4.5 and CART, with 20, 7.69, and 13.46 percent less error rates.	✓	✓	✓	✓
[35]	Three approaches on the (292) child, (104) adolescent, and (704) adult data sets	NB, CNN, SVM, LR	Accuracy	CNN = 99.53% Adult 98.30% children 96.88% adolescent	✓	✓	✓	×
[36]	From the University of California Irvine ML repository, three methods were used on data sets for children, adolescents, and adults	SS, RFE, Multilayer Perceptron (MLP) Quadratic Discriminant Analysis (QDA), Random Forest, SVM	Accuracy, sensitivity, and specificity	SS, RFE=100%, 9% child 100%, 97% adolescent 100%, 97% adult	✓	✓	✓	×
[29]	There are three dataset groups, each with 29 Chinese individuals in the AQ-10	Data driven feature extraction method and a SVM to do the classification.	Accuracy	88.51%	✓	✓	✓	×
[39]	Single Nucleotide Variants in Non-Coding DNA Associated with ASD Found by an Out-group ML Approach	Regularized logistic regression	Accuracy	AUC-ROC values ranging from 0.600 to 0.960	✓	✓	✓	×
[37]	Three methods were used using the AQ-10 child, adolescent, and adult data sets.	Apply 27 benchmark ML classification techniques	Accuracy	MlP, SL, SMO=97%-100%	✓	✓	✓	×
[40]	The study included information from 60 adult males, including 30 pairs of biological siblings. Thirty of the volunteers had ASD, whereas the other thirty did not show the endophenotype	Sparse Logistic Regression (SLR)	AUC, Accuracy	AUC=0.78, Accuracy=75%	×	×	×	×
[33]	3 case-control study datasets containing 431 AQ-10 samples from the ASD 30 class	IML approach on the rough set theory	Accuracy	Original 78%, 75% 69%, merged 75% 70% 67%	✓	✓	✓	×

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As illustrated in Table 1, the primary purpose of employing ML classifiers is to evaluate the performance of selected features obtained from demographic datasets. Consequently, this study aims to investigate the factors that influence medical and demographic characteristics and identify the specific information that directly impacts the development of a novel prediction strategy to mitigate the potential risks associated with autism. Previous studies have demonstrated variations in ASD classification tasks, including the use of different demographic and family characteristics, as well as variations in accuracy results, regardless of overall performance variances. Additionally, machine learning techniques have primarily focused on processing demographic features related to autism from the pre-conception and prenatal periods. However, it is important to note that demographic features associated with the prevalence of ASD may differ across various environments, making it challenging to generalize findings to specific settings.

Despite extensive research on autism worldwide, limited attention has been given to exploring the medical and demographic characteristics that directly influence ASD. Furthermore, despite numerous studies conducted on this topic, none have accurately described the complete set of affected features related to medical characteristics that have a significant relationship with autism using traditional feature selection approaches, and using sufficiently large medical datasets. Moreover, there have been no studies conducted to build ML models based on integrated medical and demographic characteristics datasets using traditional feature selection approaches. Therefore, it is crucial to collect a new ASD dataset, taking into consideration the aforementioned limitations in the existing literature, and develop a comprehensive model accordingly.

3. Methodology

The methodology employed in this study presents a systematic approach to address the challenges and complexities of autism detection. The first phase of the methodology focuses on the identification and pre-processing of the ASD dataset. This involves data identification, cleaning, imputing missing values, normalization, and transformation to ensure data quality and consistency. The second phase revolves around the development of the machine learning model. This includes constructing the model architecture, selecting appropriate feature selection algorithms, and training the model using the pre-processed dataset. The study follows this structured methodology to provide a comprehensive and robust approach to ASD detection and explanation. Figure 1 illustrates the two phases of the methodology, highlighting their collective contribution to the study.

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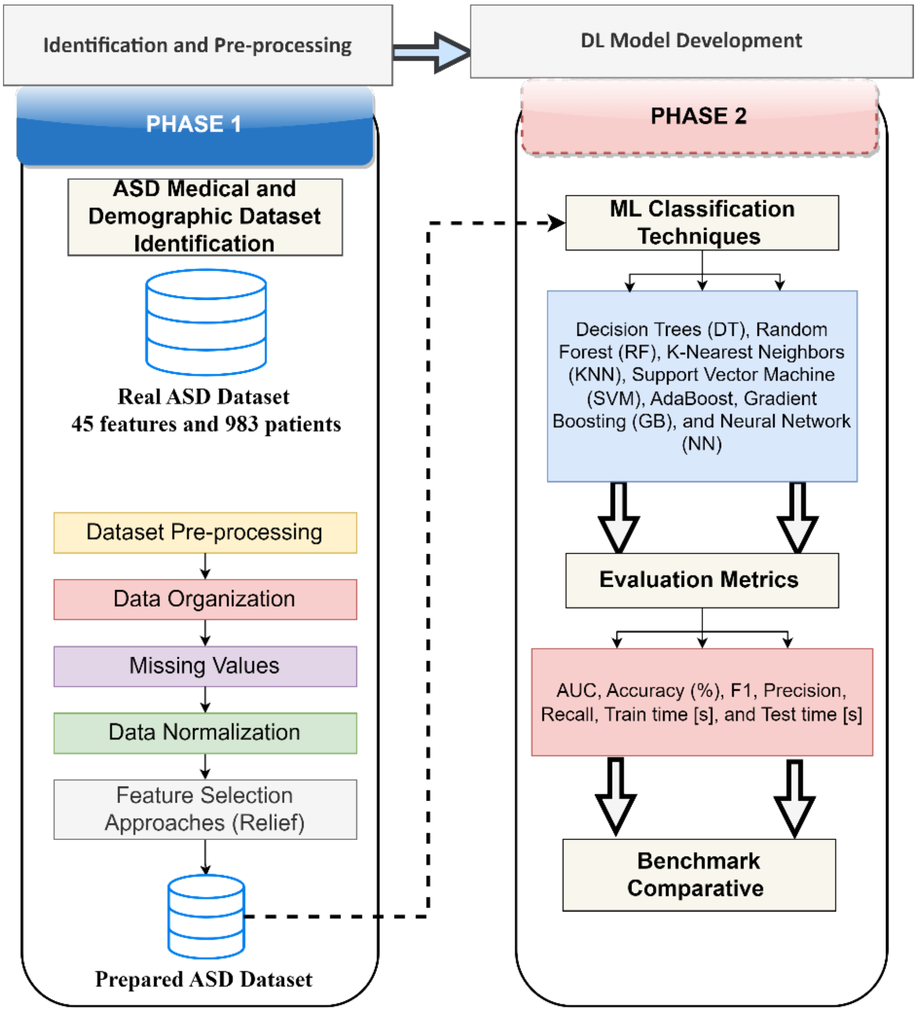

Figure 1 Integration methodology phases for ASD detection

3.1. PHASE 1: Data Identification and Pre-processing

The first phase of the study focuses on data identification and pre-processing for the ASD dataset. The ASD dataset includes 45 features and 983 patients. This involves understanding the types of features present in the dataset and implementing various pre-processing stages to prepare the data for further analysis. The outcome of this pre-processing phase is a prepared ASD dataset that includes the relevant features for utilization in the subsequent ML model development. By addressing missing data, normalizing the features, and selecting the most informative ones, the dataset is optimized for accurate and reliable analysis of ASD.

3.1.1. Dataset Identification

To begin, the types of features in the ASD dataset are examined. These features can be categorized into medical and demographic data types, each providing valuable information related to ASD. The dataset with the required descriptions are illustrated in our previous studies [30][41]. The utilized ASD dataset includes the following features:

1. **Degree**: A medical feature represented by numerical data.
2. **Sex**: A demographic feature represented by categorical data.
3. **The patient's blood group**: A medical feature represented by categorical data.
4. **Mother blood group**: A medical feature represented by categorical data.
5. **Father blood group**: A medical feature represented by categorical data.
6. **Kinship**: A demographic feature represented by categorical data.
7. **Toxoplasmosis**: A medical feature represented by categorical data.
8. **Unnecessary drugs**: A medical feature represented by categorical data.
9. **Folic acid**: A medical feature represented by categorical data.
10. **Complications of childbirth for the mother**: A medical feature represented by categorical data.

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11. **Premature baby**: A medical feature represented by categorical data.
12. **Jaundice**: A medical feature represented by categorical data.
13. **Smells food**: A demographic feature represented by categorical data.
14. **Taste the food**: A demographic feature represented by categorical data.
15. **Afraid of loud sounds**: A demographic feature represented by categorical data.
16. **Describe**: A demographic feature represented by categorical data.
17. **Crying for no reason**: A demographic feature represented by categorical data.
18. **Kisses with a sound**: A demographic feature represented by categorical data.
19. **If the door of the house is opened, he escapes**: A demographic feature represented by categorical data.
20. **Hearing the bell sound**: A demographic feature represented by categorical data.
21. **Diapers**: A demographic feature represented by categorical data.
22. **Hygiene skills**: A demographic feature represented by categorical data.
23. **Responds when parents call by name**: A demographic feature represented by categorical data.
24. **Routing things**: A demographic feature represented by categorical data.
25. **D3**: A medical feature represented by numerical data.
26. **B12**: A medical feature represented by numerical data.
27. **Zinc**: A medical feature represented by numerical data.
28. **Marital relationship**: A demographic feature represented by categorical data.
29. **Blood group match**: A medical feature represented by categorical data.
30. **Maternal diseases during pregnancy**: A demographic feature represented by categorical data.
31. **Complications of childbirth**: A demographic feature represented by categorical data.
32. **Chew food before eating it**: A demographic feature represented by categorical data.
33. **Annoying by clothing tag**: A demographic feature represented by categorical data.
34. **Flapping**: A demographic feature represented by categorical data.
35. **Runaway out of home**: A demographic feature represented by categorical data.
36. **Freaks out about himself**: A demographic feature represented by categorical data.
37. **Follow orders**: A demographic feature represented by categorical data.
38. **Improper Laughing**: A demographic feature represented by categorical data.
39. **Mingles with children**: A demographic feature represented by categorical data.
40. **Is there a language?** A demographic feature represented by categorical data.
41. **Pointing with the index finger**: A demographic feature represented by categorical data.
42. **Dose not response to his name**: A demographic feature represented by categorical data.
43. **Arrange things in one row**: A demographic feature represented by categorical data.
44. **Moving forward and backward continuously**: A demographic feature represented by categorical data.
45. **Intensity**: A medical feature represented by categorical data.

As observed in the above points, out of the 45 medical and demographic features, only 4 features ('degree', 'D3', 'B12', and 'Zinc') belong to the numerical data type, while the remaining features fall under the categorical data type. This classification analysis of the data types is crucial for selecting the appropriate feature selection method. Additionally, here is a detailed description of some features belonging to both categorical and numerical data types

1. **Medical Features**:
    a. 'The patient's blood group,' 'mother blood group,' and 'Father blood group' are medical features that categorize the blood groups into 8 categories: 1= A+, 2= B+, 3= O+, 4= AB+, 5= O-, 6= A-, 7= AB-, and 8= B-.
    b. Toxoplasmosis,' 'Unnecessary drugs,' 'folic acid,' 'Complications of childbirth for the mother,' 'premature baby,' 'Jaundice,' and 'blood group match' are medical features presented in binary categories: 0 for "no" and 1 for "yes."
    c. The 'intensity' medical feature is categorized into 6 levels (ranging from 0 to 6) to indicate the infectious status.
2. **Demographic Features**:
    a. 'Chew food before eating it,' 'Does not respond to his name,' 'Arrange things in one row,' and 'Pointing with the index finger' are demographic features presented in binary categories: 0 for "no" and 1 for "yes."
    b. 'Marital relationship' is a demographic feature with 4 categories: 1= Not good, 2= Yes, 3= Separate, and 4= Dead.
    c. The remaining demographic features are also presented in binary categories: 0 for "no" and 1 for "yes."

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By understanding the nature of these features and their respective categories, appropriate feature selection methods can be chosen for further analysis.

3.1.2. Dataset Preprocessing

After identifying the feature types in the ASD dataset, several preprocessing stages are applied. The first stage involves handling missing data. Subsequently, normalization is performed using the Min-Max algorithm, which is a widely used method for scaling numerical data. Finally, a feature selection approach is applied to the dataset. The specific steps involved in the preprocessing solution are described below.

Model-based for Imputing Missing Data

Upon analyzing the ASD dataset, it was observed that certain features contain missing values, as depicted in Figure 2. Missing or unknown data is a common drawback that ML techniques need to deal with when solving real-life classification tasks. With a dataset comprising 983 cases, the presence of these missing values can introduce bias and inaccuracies in the results of the developed model. To address this issue, it is crucial to prepare and preprocess the dataset prior to utilizing it in the ML model. Model-based imputation techniques are employed to estimate and fill in the missing values, thereby ensuring that the dataset is complete and ready for analysis.

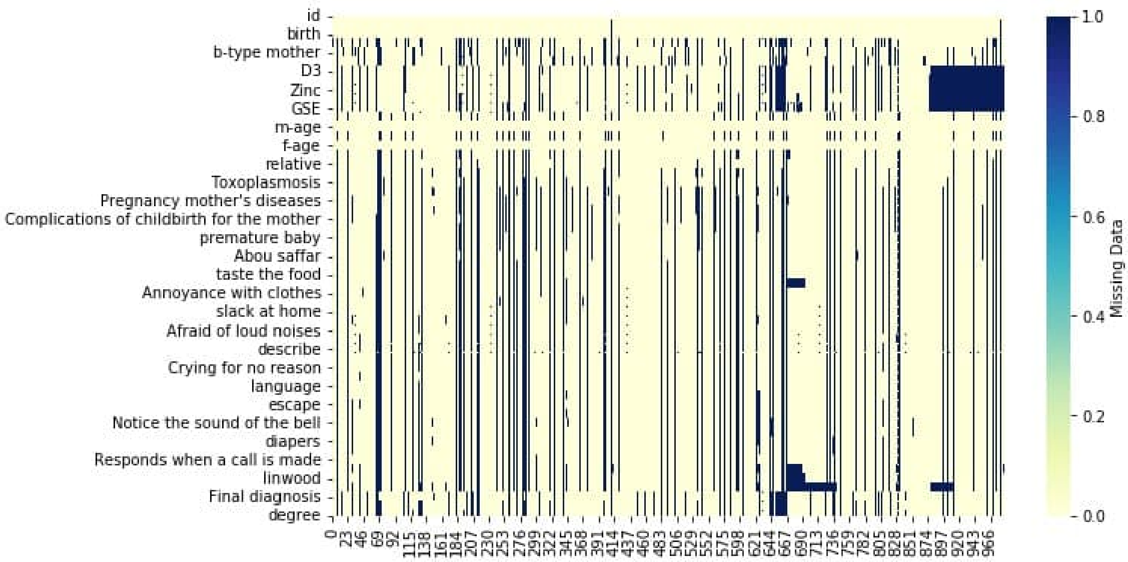

Figure 2 Dataset with sample missing values

A model-based approach involves creating a predictive model for each attribute to estimate the missing values based on the available data. By utilizing information from the dataset, these imputation methods provide more accurate estimates for the missing values. The preprocessing steps required for the ASD dataset are as follows:

- **Conversion Process**: This step involves converting string values representing the data of features into numerical values. By converting the data type to numerical, the ML model can handle these features appropriately.
- **Ignore Fake Data Process**: This process aims to remove features that contain fake data in the dataset. These features are excluded before the feature selection step as they do not contribute to the results of the feature selection process.
- **Apply Missing Data Process**: As mentioned earlier, the mean imputation technique is applied to fill in all missing values in the dataset. This technique estimates the missing values based on the mean value of the available data.

Normalization

In addition to addressing missing data through model-based imputation, the ASD dataset undergoes a normalization process to ensure that the data is scaled appropriately for analysis. Normalization is a common preprocessing technique used to bring the numerical features within a standardized range, typically between 0 and 1, or -1 and 1. This step is essential because it prevents features with larger value ranges from dominating the analysis and introduces consistency in the scale of different features. In this study, the Min-Max algorithm is applied for normalization, which is a widely used approach. The Min-Max algorithm rescales the values of each feature to a specific range by subtracting the minimum

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value and dividing by the difference between the maximum and minimum values. This process ensures that all numerical features are transformed to a common scale, preserving the relative differences between the data points.

Feature Selection Approaches

Feature selection is a critical step in building an effective ML model as using irrelevant or redundant features can potentially degrade the prediction performance. In this study, feature selection plays a crucial role in selecting the most relevant medical and demographic features for the ML model development. The feature selection process considers class-labeled datasets and evaluates the correlation between the medical and demographic features and the target class. The goal is to identify the features that have a strong relationship with the target class and contribute significantly to the prediction task.

In this study, the Filter feature selection approach is adopted, which ranks the features based on their performance measure without considering the specific ML algorithm used for modeling. This approach is computationally efficient and provides a quick way to identify the most informative features. The Relief approach is used to accomplish feature selection, taking into account the ASD dataset's data type (numerical and categorical). A popular filter-method approach called Relief is especially sensitive to feature interactions. Relief computes a feature score for each feature based on its relevance to the target class. Relief was initially developed for binary classification problems with discrete or numerical data. This score can be used to rank the features and select the top-scoring ones for further analysis. By applying the Relief method, the most relevant medical and demographic features are identified, which will be utilized in the subsequent phases of ML model development. These selected features enhance the model's accuracy and improve the interpretability of the results. With the completion of the feature selection stage, all the necessary pre-processing steps have been applied to the dataset, ensuring that the ML model can be effectively handled and developed in the next phase.

3.2. PHASE 2: Model Development

In this phase, the ML model is developed using supervised ML algorithms based on the selected medical and demographic features. The goal is to create a prediction model for ASD detection using comprehensive and well-investigated algorithms. Seven supervised ML algorithms are employed in this study to improve autism detection and create a robust model. These algorithms include: Decision Tree, Random Forest, 3) k-nearest neighbors, Support Vector Machines (SVM), Adaboost, Neural Network, and Gradient Boosting. By utilizing these algorithms, the study aims to address the ASD detection problem by exploring multiple approaches. The inclusion of these seven algorithms allows for a comprehensive analysis and comparison, as no previous studies have presented a detection model based on all seven algorithms in the context of traditional machine learning approach without giving weights to the ASD dataset features.

To evaluate the performance of the developed models, performance evaluation metrics are utilized. These metrics assess the effectiveness and performance of the classification models on the test dataset. The selected metrics for evaluation include:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Precision = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Recall = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$F1 = 2.\frac{precision.recall}{precision+recall} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$\text{AUROC: } \frac{TP}{TP+FN},\ FPR = \frac{FP}{FP+TN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

These metrics provide valuable insights into different aspects of the model's performance. By evaluating the models using cross-validation sampling and the aforementioned metrics, the study can assess their accuracy, precision, recall, F1 score, AUROC, and test time in seconds. Formulas (1) to (5) are used to calculate the performance metrics for the seven classifiers. TP represents true positives, TN denotes true negatives, FP represents false positives, and FN indicates false negatives.

4. Results and Discussion

This section presents an overview of the results obtained from the two phases implemented in the proposed methodology. The results are discussed in three subsections, providing insights into each phase and their implications. The first subsection presents the results of the ASD data pre-processing phase. The presented results shed light on the quality and reliability of the pre-processed dataset, which is essential for accurate analysis and modeling. The second subsection

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focuses on the results of the model development phase. Seven integration models were trained and evaluated using the pre-processed dataset. The outcomes of this phase reveal the performance and effectiveness of each model in ASD detection. Key metrics such as AUC, Accuracy (%), F1, Precision, Recall, Train time [s], and Test time [s] are reported, providing a comprehensive assessment of the model's capabilities. In the third subsection, the results of the benchmark comparative analysis are presented. This analysis compares the performance of the proposed methodology with other existing approaches. The outcomes of the benchmark study contribute to a better understanding of the methodology's strengths and weaknesses, as well as its potential applications in clinical settings.

4.1. Pre-processing Result

The pre-processing phase is crucial for achieving accurate results and successful predictions in ML techniques. ML algorithms require certain characteristics from the data, including numerical format, absence of statistical noise and errors, and homogeneity. Pre-processing ensures that the data is in a suitable form for analysis by addressing issues such as missing data, errors, and inconsistencies. To begin with, raw data cannot be used directly as it may contain errors or missing values that can hinder accurate predictions. It is necessary to clean and preprocess the data before applying ML algorithms. Domain expertise can help identify erroneous data, and data quality checks are performed to remove or correct any inconsistencies. Missing data poses a significant challenge as it can lead to biased parameter estimation, loss of information, decreased statistical power, increased standard errors, and weakened generalizability of findings.

In this study, missing values in the dataset were addressed by replacing them with new values. The approach used in this study was to impute missing values with the mean value. This means that for each feature with missing values, the mean value of the available data for that feature was used as a replacement. After applying the missing data processing step, the dataset was prepared, and missing values were handled for the 983 cases in the study. The result of the missing value processing can be seen in Figure 3, which provides an overview of the missing data distribution in the dataset.

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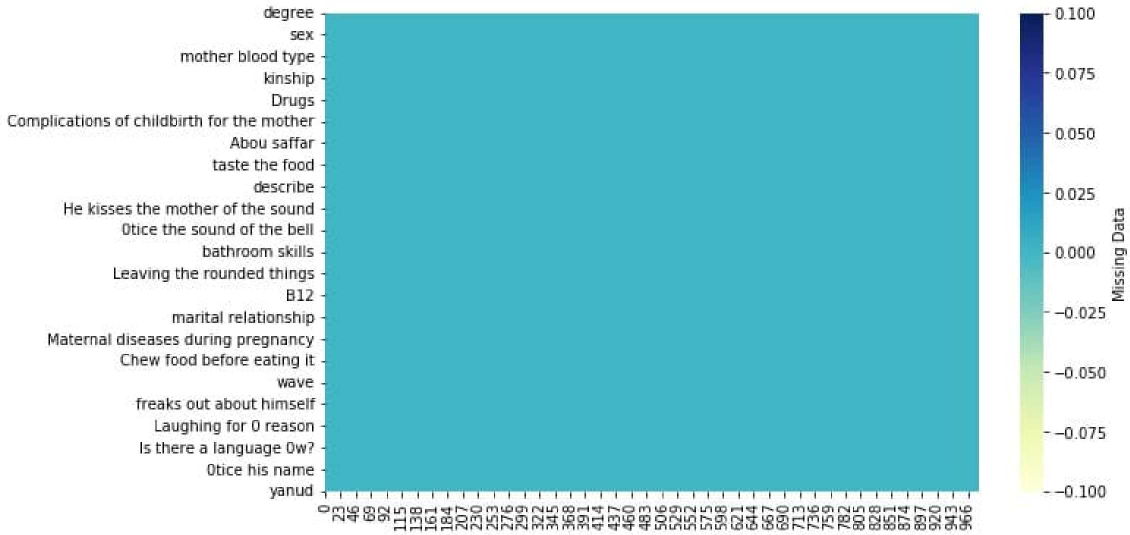

Figure 3 Dataset imputing missing value results

The next step in the pre-processing phase is normalization. In this study, the min-max scaling technique was applied, which scales the data to a range of 0 to 1. This normalization method ensures that all features have a similar scale and prevents any particular feature from dominating the analysis due to its larger magnitude. Table 2 provides a sample result of the data normalization process, showcasing the transformed values of the features after applying min-max scaling.

Table 2 Sample of ASD dataset after normalization

D3	B12	Zinc	Marital relationship	Blood match	Maternal diseases during pregnancy	Complications of childbirth	Chew food before eating it	Chew food before eating it	Moving forward and backward continuously
6.3	392.9	90	1	0	1	0	1	0	1
7.2	240.3	64.8	0	0	1	0	1	0	1
13.6	50	40.1	1	0	1	1	1	1	0
17.15	396	120	1	0	1	0	1	1	0
17.6	419	71	1	0	1	1	1	1	1
7.87	517	70	1	0	0	0	1	1	1
30.1	307.7	80	1	0	1	0	1	0	1

Regarding feature selection, the original dataset initially contained 45 features, as mentioned in Section 3.1. However, not all of these features have a significant impact on the intensity of ASD diseases. Therefore, a feature selection approach was employed to identify the most relevant features for the ML model. The Relief method was applied for feature selection on the pre-processed dataset. This approach evaluates the importance of each feature based on its relevance to the target variable. As a result, 35 features were selected for further analysis, while 10 features were excluded as they were deemed ineffective in determining the intensity of ASD diseases. Table 3 presents the results of the feature selection process, indicating the selected features. Features with negative or weak values, such as 'B12', 'Responds when parents call by name', 'Toxoplasmosis', 'Moving forward and backward continuously', and 'Hearing the bell sound', were excluded from the selected features.

Table 3 ASD dataset feature selection results

ASD Features	Feature Selection Results
Pointing with the index finger	0.1028
Afraid of loud sounds	0.0836
Freaks out about himself	0.0692
Crying for no reason	0.0665
Improper Laughing	0.0590
Degree	0.0543
Maternal diseases during pregnancy	0.0475
Arrange things in one row	0.0388
Chew food before eating it	0.0380
Jaundice	0.0377
Is there a language?	0.0362
Follow orders	0.0347
Kisses with a sound	0.0311
If the door of the house is opened, he escapes	0.0301
Smells food	0.0291
Runaway out of home	0.0241
Annoying by clothing tag	0.0220
Sex	0.0211
Hygiene skills	0.0164
Mother blood group	0.0146
Dose not response to his name	0.0135
Kinship	0.0131
Nodding	0.0130
Complications of childbirth for the mother	0.0120
Routing things	0.0111
D3	0.0103
Diapers	0.0050
Zinc	0.0045
Blood group match	0.0043
The patient's blood group	0.0023
B12	0.0009
Responds when parents call by name	-0.0011
Toxoplasmosis	-0.0046
Moving forward and backward continuously	-0.0094
Hearing the bell sound	-0.0136

The feature selection results provide insights into the most influential features for predicting the intensity of ASD. Among the selected features, some notable ones include "Pointing with the index finger," "Afraid of loud sounds," "Freaks out about himself," and "Crying for no reason." These behavioral characteristics show a strong correlation with ASD severity. Social and communication-related features such as "Improper Laughing," "Is there a language?," "Follow orders," and "Kisses with a sound" are also identified as important indicators of ASD intensity. Maternal factors like "Maternal diseases during pregnancy" and "Complications of childbirth for the mother" are relevant in assessing the severity of ASD. Sensory sensitivities and repetitive behaviors are represented by features such as "Annoying by clothing tag," "Smells food," and "Runaway out of home," which contribute to the intensity of ASD symptoms. These findings highlight the multifaceted nature of ASD and provide valuable insights for future research and model development.

4.2. Model Development Result

The results presented in Table 4 demonstrate the performance of the trained models. After performing data preparation and processing steps, a total of seven machine learning models were constructed using various libraries such as Sklearn, Tensorflow, and others. These models include DT, RF, GB, KNN, SVM, AdaBoost, and Neural Network. Each algorithm brings its unique capabilities and characteristics to the models. The models were trained on the preprocessed data to achieve the best possible performance. It is important to note that specific performance metrics and evaluation results from Table 3 are necessary to provide a more detailed analysis of the trained models' performance.

Table 4 Model development results of training

ML Classifiers	AUC	Accuracy (%)	F1	Precision	Recall	Train time [s]	Test time [s]
AdaBoost	0.86	83%	0.83	0.83	0.83	0.551	0.187
Gradient Boosting	0.95	87%	0.86	0.86	0.87	21.890	0.173
Neural Network	0.85	74%	0.72	0.71	0.74	11.005	0.182
Random Forest	0.89	80%	0.77	0.80	0.80	0.666	0.194
SVM	0.82	69%	0.64	0.64	0.69	4.145	0.270
DT	0.89	85%	0.85	0.84	0.85	3.054	0.022
kNN	0.65	55%	0.52	0.51	0.55	0.634	0.430

Table 4 showcases the results of model development and training using various ML classifiers. The AdaBoost classifier achieved an AUC of 0.86, with an accuracy of 83%, F1 score of 0.83, precision of 0.83, and recall of 0.83. It had a train time of 0.551 seconds and a test time of 0.187 seconds. The Gradient Boosting classifier demonstrated a high AUC of 0.95, with an accuracy of 87%. It obtained an F1 score of 0.86, precision of 0.86, and recall of 0.87. The train time was 21.890 seconds, while the test time was 0.173 seconds. The Neural Network classifier achieved an AUC of 0.85, with a lower accuracy of 74%. It obtained an F1 score of 0.72, precision of 0.71, and recall of 0.74. The train time was 11.005 seconds, and the test time was 0.182 seconds. The Random Forest classifier yielded an AUC of 0.89, with an accuracy of 80%. It obtained an F1 score of 0.77, precision of 0.80, and recall of 0.80. The train time was 0.666 seconds, and the test time was 0.194 seconds. The SVM classifier achieved an AUC of 0.82, with an accuracy of 69%. It had an F1 score of 0.64, precision of 0.64, and recall of 0.69. The train time was 4.145 seconds, while the test time was 0.270 seconds. The DT classifier attained an AUC of 0.89, with an accuracy of 85%. It obtained an F1 score of 0.85, precision of 0.84, and recall of 0.85. The train time was 3.054 seconds, and the test time was 0.022 seconds. The kNN classifier demonstrated the lowest performance among the evaluated classifiers, with an AUC of 0.65 and an accuracy of 55%. It obtained an F1 score of 0.52, precision of 0.51, and recall of 0.55. The train time was 0.634 seconds, and the test time was 0.430 seconds. These results provide a comprehensive overview of the performance of each classifier, enabling comparison and assessment of their effectiveness in the given context.

The evaluation results of the classifiers indicate that the Gradient Boosting model is the top-performing classifier for autism detection based on the selected medical and demographic features. With an impressive AUC of 0.95, the model demonstrates a high ability to differentiate between positive and negative instances effectively. This suggests that the model can accurately identify individuals with autism. The accuracy of 87% further strengthens the reliability of the model's predictions, indicating a high level of correctness. The F1 score of 0.86 reflects a good balance between precision and recall, indicating that the model can effectively minimize false positives and false negatives while identifying true positives. The precision score of 0.86 indicates the model's ability to make accurate positive predictions, while the recall score of 0.87 highlights its capability to capture a significant number of positive instances. Although the Gradient Boosting model has a relatively longer training time of 21.890 seconds, it compensates with a fast test time of 0.173 seconds, making it efficient in making predictions on new data. Overall, the Gradient Boosting model demonstrates strong predictive performance, with high accuracy, AUC, precision, and recall values. It has the potential to serve as a reliable classifier for autism diagnosis and early detection. However, it is important to consider the specific requirements and context of the application when selecting the most suitable model.

4.3. Benchmark Comparative Result

The checklist benchmarking approach is used to compare the proposed model with existing benchmark works based on three important points related to diagnosing autism. These points are evaluated and compared in Table 5 to measure the effectiveness of the proposed model.

- The first point focuses on the utilization of medical and demographic characteristics features. It determines whether the presented model integrates these features derived from feature selection approaches. The inclusion of the most affected features is crucial in implementing the ML model, and this point is assigned if the study covers one or more of these features.
- The second point examines the utilization of recommended ML algorithms. It assesses whether the study implemented the ML methods recommended by the literature for the detection model outcome. In this case, the study utilized the seven recommended ML methods.
- The third point considers the pre-processing approaches, including handling missing values, normalization, and feature selection. These steps are essential to ensure accurate results in the detection model. The study addresses the missing value issue within the ASD dataset, applies normalization techniques, and employs feature selection approaches to identify critical affected ASD features for the ML model components.

By evaluating these three points, the checklist benchmarking provides insights into how the presented model compares to other methods in terms of the utilization of medical and demographic characteristics features, the implementation of recommended ML algorithms, and the effectiveness of pre-processing approaches

Table 5 Benchmark comparative result

	Benchmark Points	Bench-mark#1 [33]	Bench-mark#2 [34]	Bench-mark#3 [35]	Bench-mark#4 [40]	Bench-mark#5 [38]	This study
1	ASD dataset with integrated medical and demographic features	×	×	×	×	×	✓
2	Utilization of recommended ML algorithms	×	×	×	×	×	✓
3	Considering of preprocessing approaches (missing, normalization, and feature selection)	✓	✓	✓	×	✓	✓
	Total score	33%	33%	33%	0%	33%	100%

The comparisons in Table 5 reveal that several benchmark works did not adequately address the comparison points. Benchmark#1, Benchmark#2, Benchmark#3, and Benchmark#5 obtained a score of 33% but did not cover any of the medical and demographic features, did not implement all ML algorithms, and lack a large-scale dataset when applying the model. Other benchmark studies also had limitations such as limited coverage of medical and demographic features and the absence of important comparison points like using a large-scale ASD dataset and implementing all ML algorithms in their models. Benchmark#4 received a score of 0% as it only used one ML algorithm and did not consider the other comparison points. In contrast, the proposed model addressed all the important points and presented a valuable autism detection model that incorporates medical and demographic features, utilizes all recommended ML algorithms, and includes preprocessing steps. Based on the comparison results, the proposed model stands out as a comprehensive and valuable contribution to the field of autism detection, as it successfully addresses all the important points in the checklist benchmarking.

5. CONCLUSION

The presented study represents a pioneering effort in constructing a ML model using a real ASD dataset, which includes 45 features and 983 patients. The dataset comprises both medical and demographic features, known to be associated with ASD. In this study, the main objective was to predict the intensity of autism using an ML model, and a traditional feature selection method was employed instead of constructing an ML model based on weighted features or the intersection of different ML methods and feature selection approaches. The decision to utilize a traditional feature selection method was based on several factors. Firstly, traditional feature selection methods have demonstrated effectiveness in selecting relevant features that contribute to the predictive performance of ML models. By employing this method, the study aimed to identify the most influential features associated with ASD and include them in the ML model. Secondly, constructing an ML model based on weighted features or the intersection of different ML methods and feature selection approaches can be complex and resource-intensive. Given the scope and objectives of this study, a traditional feature selection method was deemed more practical and feasible. The implications of the constructed ML model are significant, as it has the potential to address challenges in current diagnostic practices. The pre-processing stages applied to the dataset resulted in accurate data processing and high accuracy percentages across the ML methods. The developed methodology can be extended to other medical cases, overcoming detection challenges beyond ASD. While alternative approaches, such as constructing an ML model based on weighted features or utilizing the intersection of different ML methods and feature selection approaches, may offer benefits, the decision to employ a traditional feature selection method was driven by practical considerations and the goal of identifying the most influential features associated with ASD. To the best of our knowledge, this study represents the first attempt to detect ASD based on medical tests and demographic features. Early detection based on the developed model holds the potential for physicians and medical staff to analyze serial measurements in ASD medical research, providing valuable insights and enabling proactive interventions. In summary, the utilization of a traditional feature selection method in this study allows for the identification of relevant features associated with ASD and contributes to the development of an ML model with potential applications in improving diagnostic practices and early detection. Future research may explore alternative approaches to further enhance the model's performance and extend its applicability

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Data availability

The datasets analyzed during the current study are available in the Trauma Audit and Research Network repository, https://www.kaggle.com/ in [42].

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