A NOVEL ENSEMBLE META-FEATURES INTEGRATION TECHNIQUE FOR AUTISM SPECTRUM DISORDER DETECTION

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ABSTRACT

Autism Spectrum Disorder (ASD) manifests as a multifaceted neurodevelopmental condition marked by difficulties in social interaction, communication, and repetitive behaviors. This paper proposes novel techniques for the detection of ASD using a combination of conventional ML algorithms and advanced ensemble techniques. Leveraging three datasets sourced from the UCI Repository, representing distinct age groups—adults, adolescents, and children, innovative approaches are introduced to enhance ASD diagnosis. After the collection of data, data preprocessing is performed. Later, the top features in each dataset are analyzed, providing insights into the most discriminative features for ASD detection. Initially, conventional ML algorithms, including logistic regression, KNN, SVM, decision trees, random forests, AdaBoost, and gradient boosting, are applied to establish a baseline for comparison. Subsequently, the effectiveness of ensemble techniques, including Bagging Meta-learner (BMA), Stacked Generalization, Stacking Classifier, and Voting Classifier, in improving detection performance is explored. Experimental findings demonstrate that the proposed ensemble techniques consistently outperform individual models across all datasets. Later, a novel ensemble meta-features integration technique was introduced, combining predictions from individual ensemble models to enhance ASD detection performance achieving higher accuracy, precision, recall, and F1-score. Finally, extended analysis was conducted to classify ASD cases into age-specific categories using ML models, achieving good results. Moreover, the techniques proposed in this research offer scalability and adaptability, suitable for implementation in diverse clinical settings. This research contributes to advancing ML-based approaches for ASD diagnosis, offering novel techniques that can potentially enhance clinical decision-making.

Keywords: *Autsim spectrum Disorder, Data Preprocessing, Ensemble Learning, Machine Learning*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complicated neurological disorder that affects social interaction, communication, and several activities. Diagnosing ASD is a multifaceted process that requires careful consideration of various factors, including age, developmental stage, and individual differences. The challenges associated with diagnosing ASD are further compounded by the variability in symptoms and presentation across different age groups. In adults, symptoms may be masked or camouflaged, making it challenging to differentiate ASD from other mental health conditions or personality traits. Adolescents, undergoing rapid developmental changes and social transitions, may exhibit fluctuating or evolving symptoms, complicating the diagnostic process. Similarly, diagnosing ASD in children requires specialized assessments and expertise to distinguish typical developmental variations from early signs of ASD. Clinical observations and standardized evaluations may miss subtle or uncommon symptoms, resulting in underdiagnosis or misinterpretation, especially in disadvantaged or underrepresented areas. Additionally, these evaluations are subjective, resulting in inconsistent diagnostic results. Recently developed ML and data analysis methods have improved ASD diagnosis. ML models may find patterns and correlations in huge clinical and behavioral datasets that conventional diagnostic methods cannot. In this paper, several ML techniques are applied for the detection of ASD in different age groups.In this paper, alongside addressing the complexities of ASD diagnosis, the utilization of ML techniques offers a promising avenue for enhancing diagnostic accuracy across diverse age groups, aligning with the burgeoning field of precision medicine.

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In [1], the authors proposed a scan path-based ASD detection approach based on dynamic gaze distribution changes. Two similarity metrics were used to compare feature space and gaze behavior patterns between ASD and usual development (TD), utilizing four sequence characteristics from scan paths. The gaze patterns of ASD children were more individualistic, with variances in attention duration and vertical spatial distribution. LSTM networks beat classical classification. However, while the study provided valuable insights into gaze behavior patterns, it primarily focused on a specific aspect of ASD detection and did not explore broader diagnostic techniques.[2] presented a systematic review of existing literature on the use of machine learning for ASD detection and proposed a diagnostic tool. The authors claimed that the utilization of transfer learning techniques improved the detection of ASD successfully. Although transfer learning is acknowledged as beneficial, the review could have provided more in-depth analysis and comparison of different transfer learning approaches for ASD detection.In [3], logistic regression, XGboost, SVC, and Naive Bayes were used to investigate ASD detection parameters using open-source datasets. The most effective was XGBoost. Analytical methods show that machine-learning may accurately predict autism spectrum disorder status when optimized. These results suggest that these models might diagnose ASD early, improving intervention chances. All datasets, including cross-validation, performed better with XGBoost.The study highlights the effectiveness of XGBoost in ASD detection, but a deeper exploration of the limitations and challenges of each algorithm could provide more comprehensive insights. In [4], the authors trained two ML classifiers, logistic regression and SVM, locally to classify ASD variables and diagnose ASD in children and adults using a FL approach. These classifiers' outputs were sent to a central server where a meta classifier was trained to identify the best method for detecting ASD in children and adults due to FL. For feature extraction, four ASD patient datasets from various sources had more than records of afflicted children and adults.While the study introduces a federated learning approach for ASD detection, it could benefit from discussing potential privacy and data sharing concerns associated with this method.

Machine learning was applied in [5] to increase diagnostic precision and time. Datasets were analyzed using SVM, Random Forest, Naïve Bayes, Logistic Regression, and KNN models, resulting in predictive models. Results show logistic regression has the greatest accuracy for the chosen dataset. Convolutional neural networks and particle swarm optimization were used to diagnose ASD in [6]. Initial preparation tackles missing data. SVM, NB, LR, and PSO-CNN are evaluated on ASD screening datasets. PSO-CNN outperformed other approaches in accuracy, especially for missing data. [7] used KNN, Logistic Regression, Decision Trees, Random Forest, Naive Bayes, and XGB Classifier to detect ASD based on user input. A classification method was given in [8] to study functional brain connections utilizing the newly built database ABIDE II, which pooled multisite data from three locations. Several classification techniques were used, including SVM, LR, and RF. RF surpassed the other two strategies with an ideal classification accuracy of 75%, much higher than earlier efforts. [9] used four feature scaling (FS) techniques and eight machine learning algorithms to classify datasets. Statistical evaluations determined the optimum classification and FS approaches for four typical ASD datasets. In [10], MRI brain scans were used to identify autism conditions using a deep CNN with Dwarf Mongoose optimized residual network (DM-ResNet). Non-brain tissues were eliminated before segmentation utilizing hybrid Fuzzy C Means (FCM) and Gaussian Mixture Model. DM optimized ResNetclassified features collected by VGG-16 networks.

[11] employed ML models to diagnose ADHD children with ASD using handwriting characteristics. Japanese children's handwriting was analyzed statistically. Analyzing these characteristics trained ADHD detection ML systems. The most accurate was the Random Forest classifier. This research shows handwriting patterns may distinguish ADHD, ASD, and healthy youngsters. [12] refined GEI with Joint Energy Image (JEI), which maintained just joint locations from video sequences. Prior to color mapping, depth was represented in binary pictures. JEI combined temporal and depth data into 2D. A CNN and machine learning models were preprocessed using Principal Component Analysis before JEI. CNN accuracy increased on the main and secondary datasets. In [13], an app was created to diagnose autistic and non-autistic children using ResNet-50 and Xception modules. The ResNet-50 approach outperformed traditional methods in accuracy. [14] tested a hybrid, deep CNN-based transfer learning model to diagnose childhood autism. Various transfer learning techniques were used to extract features for classifiers. The most accurate was ResNet101V2 using SVM and

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Logistic Regression. The suggested multi-valued autism classification model worked well, possibly helping future research and therapeutic applications. [15] evaluated ML-based ASD diagnostic literature over the previous 5 years, establishing a taxonomy of the research environment and addressing key topics. It covered ML's classification process, MRI, representative studies, techniques, and biomarkers.

Using the ABIDE dataset, ML algorithms were used to identify ASD in normal people [16]. The VM, LSTM, and CNN algorithms were examined. The best algorithm was CNN, with 95% accuracy. In [17], AI and DL screen children and adults for autism. Compared to classic and hybrid deep learning models, the proposed models proved superior. [18] used multiple feature selection methods on ASD datasets of toddlers, children, adolescents, and adults. After that, prediction accuracy, kappa statistics, the f1-measure, and AUROC were used to evaluate different classifiers on these datasets. Additionally, a non-parametric statistical significance test assessed classifier performance. The authors in [19] used real-world health claims data to predict ASD risk in 18- to 30-month-olds based on their medical history. Early diagnosis and intervention are essential for improving ASD children's long-term results, however, current screening techniques are inaccurate. In [20], deep learning was studied for ASD recognition. They found face features and a CNN effective for autism detection. Face recognition utilizing automated feature extraction and CNN classification might detect autism spectrum disorder, the study found.

A novel dataset with 20 features was proposed for adult autism screening [21]. This dataset was expected to aid future studies in identifying autism's core components and classifying ASD patients. Behavioral studies suggest that the ten behavioral variables (AQ-10-Adult) and ten personality factors in this dataset might distinguish ASD patients from controls. [22] classified ASC patients using machine learning models based on face expressions, gaze behavior, head attitude, and speech attributes. The highest accuracy (74%) was attained with multimodal late fusion. In unimodal circumstances, face emotions (73%) and vocal characteristics (70%) worked well. We created an online SIT to gather different data for machine learning model construction, demonstrating machine learning's promise in clinical diagnosis. [23] predicted 12-36-month-old ASD with machine learning. 4-11, 12-17, and 18-year-olds were projected to have ASD. Advanced methodologies and technology were applied for ASD analysis, including Smart Autism, a smart device-based automated autism screening tool, and Genetic Variant Analysis of Boys with Autism. An ML-based approach was created to detect early ASD indications in youngsters [24]. SVM and RF algorithms helped the system categorize ASD data more accurately than previous techniques. In [25], computer vision tools were explored to assess ASD children's abilities and emotions during videotaped intervention sessions. Using 300 films, three deep learning-based vision models were created: activity comprehension, joint attention recognition, and emotion detection. On real-world footage, these models achieved 72.32%, 97%, 93.4%, and 95.1% accuracy. [26] divided ASD results into behavioral analysis, picture processing, and speech processing. The final section compared the efficiency of autism detection models or algorithms in each category.

Despite the multitude of machine learning (ML) models developed for ASD detection, many fall short in providing robust and accurate diagnoses. Existing approaches often struggle with issues related to accuracy, scalability, and suitability for diverse clinical environments. However, this study introduces innovative techniques that integrate conventional ML algorithms with advanced ensemble methods, notably through a novel ensemble meta-features integration approach. By enhancing detection performance and offering scalability and adaptability, these novel approaches have the potential to revolutionize clinical decision-making in ASD diagnosis.

2. METHOD

The proposed framework for ASD detection is shown in Figure 1. In this work, data collection involved leveraging three distinct datasets sourced from the UCI Machine Learning Repository, representing different age groups: adults, adolescents, and children. The datasets served as the foundation for exploring the autism spectrum disorder (ASD) detection. After that, data preprocessing was done. In data preprocessing, missing values and irrelevant features are removed. Later, top feature analysis was conducted. To establish a baseline for comparison, conventional machine learning (ML) algorithms, including logistic regression, k-nearest neighbors, support vector machines, decision trees, random forests, AdaBoost, and gradient boosting, were applied.

The performance of each model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Later, four ensemble

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techniques were employed, including bagging meta-learner (BMA), stacked generalization, stacking classifier, and voting classifier. These techniques were applied individually, with predictions from each model combined using a meta-learner and a novel feature merging approach. The meta-learner was trained using predictions from individual ensemble models as input features, and the performance of the meta-ensemble model was evaluated using standard metrics. Experimental evaluation was performed to assess the effectiveness of each technique and the meta-ensemble approach. The performance of ensemble techniques was compared against individual ML models and the meta-ensemble model.

Additionally, ASD classification was conducted based on three age groups using ML algorithms. This classification was performed to classify the samples into different age groups based on the input characteristics. In the discussion and conclusion sections, the experimental findings were discussed, highlighting the strengths and weaknesses of each technique and the novel feature merging approach. Insights into the potential implications of the proposed ensemble techniques and novel feature merging for ASD diagnosis were provided.

2.1. ASD Data Collection

The ASD dataset was gathered from the UCI repository. Three datasets, namely Autism-Adult-Data [27], Autism-Adolescent-Data [28], and Autism-Child-Data [29], were collected from UCI. Three datasets were utilized for autism screening, comprising 20 features, including ten behavioral traits (Q-Chat-10 [29]) and ten individual characteristics. The 10 behavioral questions are shown in Table 1. For questions A1-A9: If the response is "Sometimes," "Rarely," or "Never," a value of "1" is assigned. For question A10: If the response is "Always," "Usually," or "Sometimes," a value of "1" is assigned. In this way, the dataset has A1 to A9 features with 0 and 1 values. The remaining features are collected through the responses of users through the app [31].

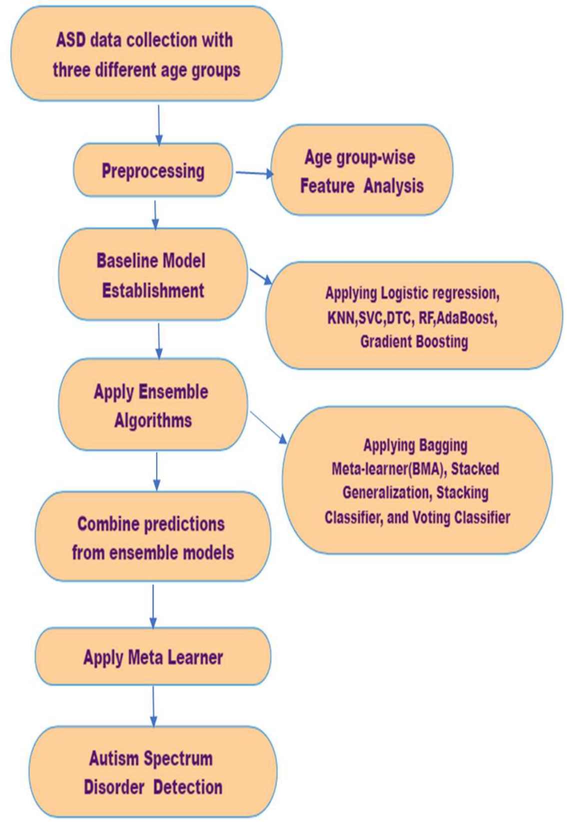

Figure1.Proposedmodel For ASD Detection

Table 1. Details Of Questions Used For Extracting Behavioral Features

Question
A1-Does the individual respond when their name is called?
A2-How easily does the individual make eye contact?
A3-Does the individual point to indicate their wants or interests?
A4-Does the individual point to share interests with others?
A5-Does the individual engage in pretend play activities?
A6-Does the individual follow others' gaze?
A7-Does the individual show signs of wanting to comfort others when they are upset?
A8-How would you describe the individual's first words?
A9-Does the individual use simple gestures, such as waving goodbye?
A10-Does the individual engage in repetitive staring behaviors without apparent purpose?

These datasets offer valuable insights into enhancing ASD detection and identifying

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influential autistic traits, addressing the scarcity of comprehensive ASD-related datasets available for analysis. The number of samples in each dataset is shown in Table 2. It shows total samples along with ASD types, yes and no.

Table 2. Details Of Datasets Used

Dataset	Number of samples with ASD as "yes"	Number of samples with ASD as "NO"	Total samples
Autism-Adult-Data	189	515	704
Autism-Adolescent-Data	63	41	104
Autism-Child-Data	141	152	292

2.2. Preprocessing

Preprocessing was conducted on three datasets, each with unique data characteristics. In the first dataset (Autism-Adult-Data), instances of missing data were identified in the 'ethnicity' and 'relation' features, denoted by '?'. Additionally, some entries in the 'age' feature were left blank. To address these issues, a preprocessing step was implemented to handle missing values appropriately. The '?' entries in the 'ethnicity' and 'relation' features were replaced with the most frequent values observed in their respective columns. Furthermore, the missing values in the 'age' feature were imputed using suitable methods such as mean or median imputation, ensuring the integrity of the dataset.Moving to the second dataset (Autism-Adolescent-Data), similar preprocessing steps were applied. Instances of missing data were observed in the 'ethnicity' and 'relation' features, again denoted by '?'. To rectify this, the same preprocessing techniques were employed, focusing on replacing the '?' entries with the most frequent values observed in their respective columns.Finally, in the third dataset (Autism-Child-Data), missing data was found in the 'relation' and 'ethnicity' features, marked by '?', while some entries in the 'age' feature were left blank. The preprocessing approach mirrored that of the previous datasets, with the '?' entries in the 'relation' and 'ethnicity' features replaced with their most frequent values, and missing values in the 'age' feature imputed using most frequent method.

2.3. Conventional ML Algorithms

To set an ASD detection baseline, many typical ML techniqueswere used. Logistic regression, a standard binary classification approach, was used to fit input characteristics to ASD probability. Simple yet effective, KNN classifies data items by their nearest neighbors' majority class. SVM found the best hyperplane to differentiate ASD from non-ASD occurrences in feature space, maximizing class margin. Recursively partitioning the data by feature values was done using decision trees, a common categorization tool. Multiple decision trees were used to create random forests to increase detection accuracy and resilience. AdaBoost, a boosting technique, trains weak learners on updated datasets to make them strong. Another boosting method, gradient boosting, stages poor learners and corrects their mistakes. Traditional ML algorithms were used to lay the groundwork for comparison with more sophisticated ensemble methods.

2.4. Ensemble Learning Algorithms

Advanced ensemble approaches are used with standard ML models to enhance Autism Spectrum Disorder (ASD) detection. Ensemble approaches use numerous models to provide a more accurate forecast. Bagging Meta-learner (BMA), Stacked Generalization, Stacking Classifier, and Voting Classifier are tested for improving ASD diagnostic accuracy and resilience. Ensemble approaches make use of base learners' variety and capacity to alleviate model shortcomings. Ensemble methods outperform individual models in accuracy, precision, recall, and F1-score measures across all datasets. Stacked Generalization is an efficient ensemble strategy for integrating base learners and optimizing detection accuracy. Adding a meta-ensemble method that combines ensemble model predictions improves detection performance. This work uses ensemble techniques to promote ML-based ASD detection methods that may improve clinical decision-making.

After applying ensemble models, the predicted results are merged, and a meta learner algorithm is applied for ASD prediction.

2.5. Identification of best features for three datasets

Feature extraction is a crucial step in machine learning, particularly in the context of autism spectrum disorder (ASD) research, where identifying the most informative attributes can lead

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to a better understanding and prediction of the condition. Leveraging the Random Forest algorithm and one-hot encoding, the approach focused on discerning the key features across diverse ASD datasets representing various age groups.By training the Random Forest Classifier and assessing feature importance, significant contributors to ASD diagnosis were discerned, shedding light on the pivotal factors that influence the disorder's manifestation. The best ten features identified in the three datasets are shown in Table 3.

From Table 3, it is observed that most of the best features are behavioral features only. For Autism-Adult-Data, top-performing features are those related to social interaction, such as the A9_Score, which evaluates an individual's use of simple gestures like waving goodbye. Additionally, A6_Score, assessing the individual's ability to follow others' gaze, and A7_Score, gauging signs of wanting to comfort others when upset, are significant indicators of social responsiveness and empathy. Features like A3_Score and A4_Score, which assess pointing behaviors to indicate wants or share interests, shed light on communication skills and joint attention abilities. These features provide valuable insights into the individual's capacity for reciprocal social interactions and communication, pivotal aspects in ASD diagnosis and intervention planning. Features such as A10_Score, focusing on repetitive staring behaviors without apparent purpose, and A1_Score, evaluating responsiveness when their name is called, offer insights into repetitive behaviors and social responsiveness, respectively, providing a comprehensive understanding of an individual's behavioral profile.

In the Autism Adolescent Data, pivotal features include A5_Score and A4_Score, indicating engagement in pretend play and sharing interests, respectively. Additionally, A10_Score and A6_Score assess repetitive behaviors and social interaction skills. Other significant features include A9_Score and A3_Score, evaluating gestures and pointing behaviors, and A8_Score and A7_Score, highlighting communication and empathetic behavior. Age serves as a critical factor in understanding developmental trajectories. Together, these features provide a comprehensive insight into adolescent behavior in the context of autism spectrum disorder.

Table 3. Best Features Including Behaviral Features

S.No	Best features in Autism-Adult-Data	Best features in Autism-Adolescent-Data	Best features in Autism-Child-Data
1	result	result	result
2	A9_Score	A5_Score	A4_Score
3	A6_Score	A4_Score	A9_Score
4	A5_Score	A10_Score	A10_Score
5	A3_Score	A6_Score	A8_Score
6	A4_Score	A9_Score	A1_Score
7	A7_Score	A3_Score	A3_Score
8	A2_Score	A8_Score	A6_Score
9	A10_Score	A7_Score	A5_Score
10	A1_Score	age	A7_score

In the Autism Child Data, significant features include A4_Score and A9_Score, reflecting the child's tendency to share interests and use gestures. A10_Score indicates repetitive behaviors, while A8_Score evaluates the child's first words. A1_Score and A3_Score highlight responsiveness and pointing behaviors, respectively, and A6_Score signifies the ability to follow others' gaze. A5_Score indicates engagement in pretend play, and A7_Score assesses empathetic behavior. These features collectively provide valuable insights into child behavior in autism spectrum disorder.

Next, best feature extraction process was performed excluding behavioral features. Table 4 shows the best features, excluding behavioral features. In table 4, some values are blank. The reason for blanks is that categorical features have several options. All options for single categorical feature is considered as a single important feature. So, autism-adult data has 5 important features, autism-adolescent data has 6 important features; and autism-child data has 7 important features. The best features from Table 3 and Table 4 are used in experimentation.

Table 4. Best Features Excluding Behaviral Features

S.No	Best features in Autism-Adult-Data	Best features in Autism-Adolescent-Data	Best features in Autism-Child-Data
1	result	result	result
2	age	contry_of_res	contry_of_res
3	contry_of_res	age	age
4	ethnicity	ethnicity	ethnicity
5	austim	jaundice	jaundice
6	-	gender	austim
7	-	-	gender

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3. RESULTS AND DISCUSSION

3.1. Applying conventional ML algorithms

To establish a baseline for comparison, a range of conventional ML algorithmswere applied, including logistic regression, KNN, SVC, decision trees, random forests, AdaBoost, and gradient boosting. Each algorithm was evaluated based on standard performance metrics, including accuracy, precision, recall, and F1-score. 80% and 20% splitting ratio is used for train and test parts in all experiments. Table 5 shows results with three datasets after applying conventional algorithms.

Figure 2a shows the results of ML algorithms with autism-adult data. Each algorithm's precision, recall, F1-Score, and accuracy are provided in Figure 2a. Precision measures the accuracy of positive predictions, with Logistic Regression leading with 95%, followed closely by SVC, KNN, Decision Tree, Random Forest, AdaBoost, and Gradient Boost. Recall, or sensitivity, indicates the model's ability to capture all positive instances, with decision tree achieving the highest at 90%. F1-Score, the harmonic mean of precision and recall, highlights Random Forest's balanced performance at 92.7%. Finally, accuracy reflects the overall correctness of predictions, with logistic regression boasting the highest at 97.3%. It I observed that all ML models given good results with autism-adult data.

Table 5. Results With ML Algorithms

S.No	Autism-Adult		Autism-Adolescent		Autism-child	
Logreg	Precision	95	Precision	92	Precision	94
	Recall	93	Recall	94	Recall	93.8
	F1	93.9	F1	92.9	F1	92.4
	Accuracy	97.3	Accuracy	96	Accuracy	97
SVC	Precision	94	Precision	93	Precision	93.5
	Recall	89	Recall	93	Recall	91
	F1	91.4	F1	93	F1	92.2
	Accuracy	95	Accuracy	94.5	Accuracy	94
KNN	Precision	93.2	Precision	93	Precision	92.5
	Recall	89	Recall	93	Recall	92
	F1	91.4	F1	93	F1	92.2
	Accuracy	94.6	Accuracy	94	Accuracy	94.6
Decision Tree	Precision	93.1	Precision	92.9	Precision	93
	Recall	90	Recall	92	Recall	91
	F1	91.5	F1	92.4	F1	91.9
	Accuracy	93.3	Accuracy	93	Accuracy	93.3
Random Forest	Precision	93	Precision	92.7	Precision	94
	Recall	92.5	Recall	93	Recall	91.5
	F1	92.7	F1	92.8	F1	92.7
	Accuracy	95.2	Accuracy	94.6	Accuracy	95.2
Adaboost	Precision	92	Precision	91.8	Precision	93
	Recall	90.4	Recall	92	Recall	92
	F1	93.2	F1	91.9	F1	92.4
	Accuracy	94.2	Accuracy	94	Accuracy	94.2
Gradient Boost	Precision	92	Precision	93	Precision	93
	Recall	91.2	Recall	92	Recall	93
	F1	91.2	F1	92.4	F1	93
	Accuracy	94.8	Accuracy	93	Accuracy	94.8

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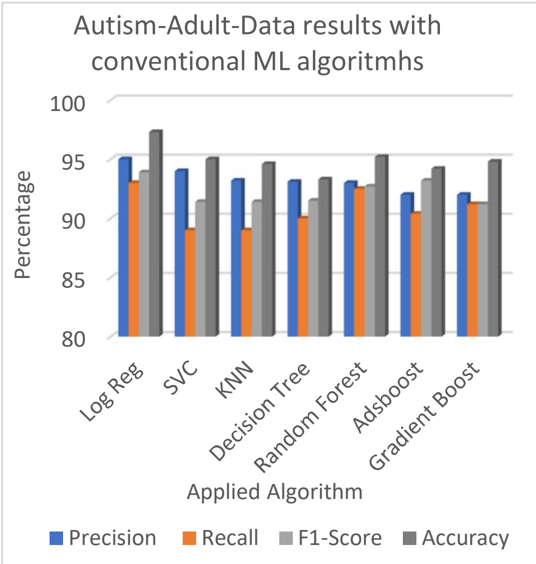

Figure 2.Results Of ML Algorithms With A) Autism-Adult-Data B)Autism-Adolescent-Data

Figure 2b shows the results of ML algorithms with autism-adolescent data. Notably, logistic regression achieves a precision of 92% and a recall of 94%, resulting in an F1-score of 92.9% and an accuracy of 96%. SVC demonstrates balanced performance across all metrics, with a precision, recall, and F1-Score of 93% and an accuracy of 94.5%. The decision tree shown a slightly lower precision at 92.9% and an F1-Score of 92.4%, with an accuracy of 93%. The remaining models also performed well for detection.

Figure 3 shows the results of ML algorithms with autism-child data. Logistic regression achieves a precision of 94% and a recall of 93.8%, resulting in an F1-Score of 92.4% and an accuracy of 97%. SVM demonstrates a precision of 93.5% and a recall of 91%, with an F1-Score of 92.2% and an accuracy of 94%. Gradient Boost shows the highest precision at 95% and recall at 94%, resulting in an F1-Score of 93% and an accuracy of 94.8%. Similarly, all the other applied models shown remarkable results with Autism-Child-Data for ASD detection.

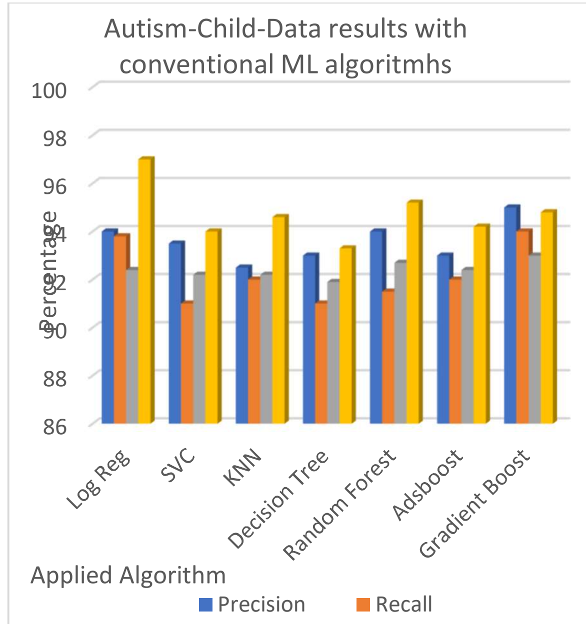

Figure3. Results Of ML Algorithms With Autism-Child-Data

3.2. Applying Ensemble Learning algorithms

Following the establishment of the baseline models, the effectiveness of ensemble techniques is explored to further enhance ASD detection performance. Four ensemble techniques namely bagging meta-learner (BMA), stacked generalization, stacking classifier, and voting classifierwere applied individually. The performance of each model evaluated using several metrices.

3.3. Applying Bayesian Model Averaging

Next, Bayesian Model Averaging (BMA) was applied as an ensemble method to enhance the detection of autism spectrum disorder (ASD). It begins by encoding categorical columns, and then the data is divided into train and test parts. Subsequently, instantiated conventional classifiers are used in Section 3.1. BMA is an ensemble technique that combines predictions from multiple models by considering their posterior probabilities based on observed data. The analysis of detection reports and accuracy scores underscored the efficacy of BMA in improving ASD detection.

3.4. Applying Stacked Generalization with Neural Networks

Next, stacked generalization with neural networks was applied to each dataset, encoding categorical

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columns and splitting the data. Then, various classifiers and a meta-learner (a neural network) were instantiated. Using KFold cross-validation with five splits, stacked predictions and trained meta-learners are generated. Finally, the performance using ASD detection reports and accuracy scores is accessed, demonstrating the effectiveness of stacked generalization with neural networks in improving ASD detection across all datasets.

3.5. Applying Voting Classifier

Next, a voting classifier was employed to enhance ASD detection across different datasets. Initially, categorical columns were encoded, and features and targets were selected from the dataset. Base models including Logistic Regression, KNN, SVC, Decision Tree, Random Forest, AdaBoost, and Gradient Boosting were instantiated for the voting classifier.

3.6. Applying Stacking Classifier

Later, a stacking classifier was applied to improve the detection of ASD. Initially, categorical columns were encoded, and features and targets were selected. Base models, including Logistic Regression, KKNN, SVM, Decision Tree, Random Forest, AdaBoost, and Gradient Boosting, were instantiated for the Stacking Classifier. The Stacking Classifier was trained and evaluated using a cross-validation strategy with five splits, generating predictions for each fold. The result report for the Stacking Classifier on each dataset was analyzed, along with mean precision, recall, and F1-score.

3.7. Results with ensemble models

The results with ensemble models are shown in Table 6. Figure 4a outlines the performance metrics of various ML algorithms with autism-adult data. The BMA algorithm displayed remarkable precision at 99%, accompanied by a recall of 97% and an F1-Score of 98%, resulting in an accuracy of 98.5%. Stacked generalization achieved a precision of 98%, with a recall of 97% and an F1-Score of 97.4%, yielding an accuracy of 98.2%. The Voting Classifier showcased a high recall of 98.5% and attained an accuracy of 98%, while the Stacking Classifier boasted a precision of 98% and a recall of 99%, culminating in an F1-Score of 98.5% and an accuracy of 99%.

Table 6. Results With Ensemble Algorithms

S.No	Autism-Adult-Data		Autism-Adolescent-Data		Autism-Child-Data	
Bayesian Model Averaging	Precision	99	Precision	99	Precision	99
	Recall	97	Recall	98	Recall	97
	F1	98	F1	98.5	F1	98
	Accuracy	98.5	Accuracy	98.6	Accuracy	98
Stacked Generalization	Precision	98	Precision	98	Precision	98
	Recall	97	Recall	97.8	Recall	98
	F1	97.4	F1	97.7	F1	98
	Accuracy	98.2	Accuracy	98	Accuracy	98
Voting Classifier	Precision	97	Precision	96	Precision	98
	Recall	98.5	Recall	97	Recall	97
	F1	96.7	F1	96.5	F1	97.5
	Accuracy	98	Accuracy	96	Accuracy	98.2
Stacking Classifier	Precision	98	Precision	96	Precision	97
	Recall	99	Recall	98	Recall	96
	F1	98.5	F1	97	F1	96.5
	Accuracy	99	Accuracy	97	Accuracy	97.5

Figure 4b shows ensemble model performance with Autism-Adolescent-Data. The BMA algorithm demonstrated exceptional precision at 99%, along with a recall of 98%, resulting in an F1-Score of 98.5% and an accuracy of 98.6%. Similarly, the stacked generalization algorithm achieved a precision of 98% with a recall of 97.8%, yielding an F1-Score of 97.7% and an accuracy of 98%. The Voting Classifier and Stacking Classifier algorithms showed slightly lower performance metrics, with precision values of 96% and recall values of 97% and 98%, respectively, resulting in

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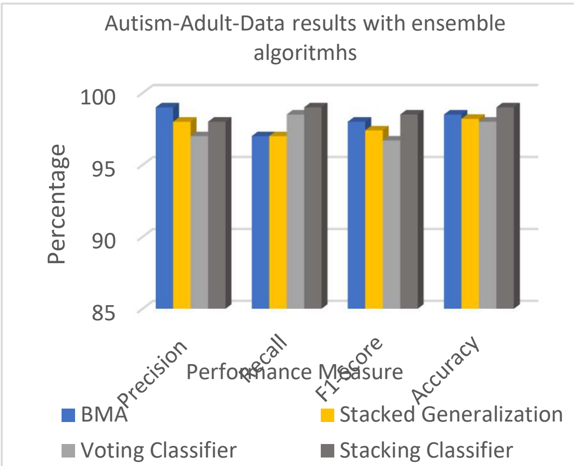
corresponding F1-Scores of 96.5% and 97% and accuracies of 96% and 97%, respectively.



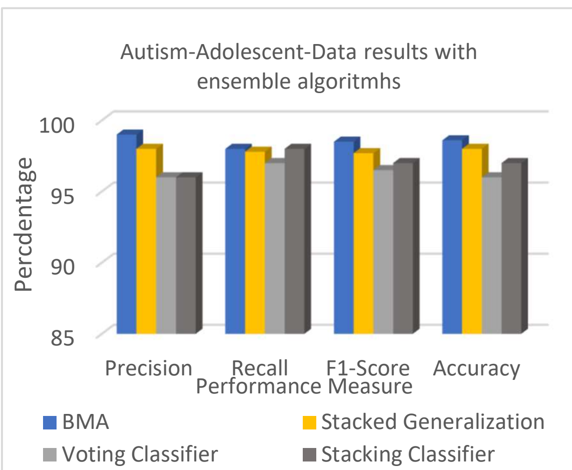


Figure 4. Results Of Ensemble Algorithms With A) Autism-Adult-Data B)Autism-Adolescent-Data

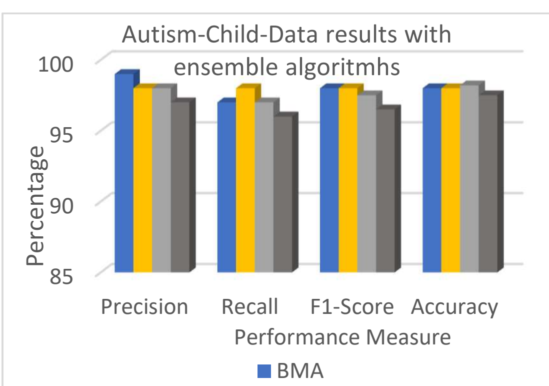


Figure5. Results Of Ensemble Algorithms With Autism-Child-Data

Figure 5 shows ensemble model performance with autism-child data. The BMA algorithm achieves exceptional precision at 99% and a recall of 97%, resulting in an F1-Score and accuracy of 98%. Similarly, the stacked generalization algorithm demonstrates strong precision and recall, both at 98%, leading to an F1-score and accuracy of 98%. The voting classifier achieves a precision of 98%, a recall of 97%, and an F1-score of 97.5%, resulting in an accuracy of 98.2%. Lastly, the Stacking Classifier yields a precision of 97% and a recall of 96%, resulting in an F1-Score of 96.5% and an accuracy of 97.5%.

3.8. Applying Novel Feature Merging Approach with Meta-Learner

In the next step, novel approach was introduced to merge features derived from individual ensemble models. This involves combining predictions from individual ensemble models using a meta-learner and integrating novel feature merging techniques. Random forest is used as a meta-learner in this approach. The meta-learner was trained using predictions from individual ensemble models as input features, and the performance of the resulting meta-ensemble model was evaluated using standard metrics. The results of Feature Merging Approach with Meta-Learner are shown in Table 7 and figure 6.

Table 7. Results With Novel Feature Merging Approach With Meta-Learner

S.No	Autism-Adult-Data		Autism-Adolescent-Data		Autism-Child-Data	
Novel Feature Merging Approach with Meta-Learner	Precision	99	Precision	99	Precision	100
	Recall	98.5	Recall	99	Recall	98
	F1	98.7	F1	99	F1	99
	Accuracy	99.2	Accuracy	99	Accuracy	98.7

The Novel Feature Merging Approach with Meta-Learner exhibited exceptional performance across various datasets related to autism spectrum disorder (ASD) detection. In the Autism-Adult Data set, the approach achieved impressive precision, recall, F1-Score, and accuracy values of 99%, 98.5%, 98.7%, and 99.2%, respectively. Similarly, in the Autism-

Adolescent Data set, the method maintained consistent high performance with precision, recall, F1-Score, and accuracy all reaching 99%.

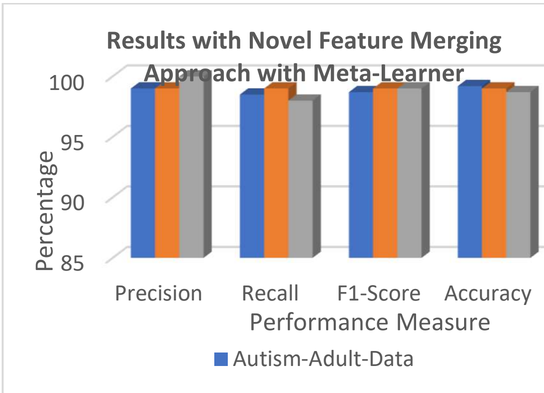


Figure6.Performance Of Feature Merging Approach With Meta-Learner

Notably, in the Autism-Child-Data set, the precision stood out as perfect at 100%, accompanied by a recall of 98%, an F1-Score of 99%, and an accuracy of 98.7%. These results underscored the efficacy of the Novel Feature Merging Approach with Meta-Learner in ASD detection across various age groups, showcasing its potential for practical implementation in clinical settings to aid in accurate and timely diagnosis.

3.9. Proposed method comparison with other models

Figure 7 shows the proposed method's accuracy comparison with other heisting models. Existing works have reported accuracies ranging from 75% to 98%. Conventional ML approaches have achieved accuracies of 75% [4] and 95% [22], while ML algorithms have shown an accuracy of 75% [8]. Additionally, conventional deep learning methods have reached an accuracy of 95% [16]. Moreover, computer vision techniques have demonstrated promising results with an accuracy of 95% [25]. In comparison, the proposed method surpasses these existing approaches, achieving an impressive accuracy of 99%. This indicates the effectiveness and superiority of the approach to ASD detection.

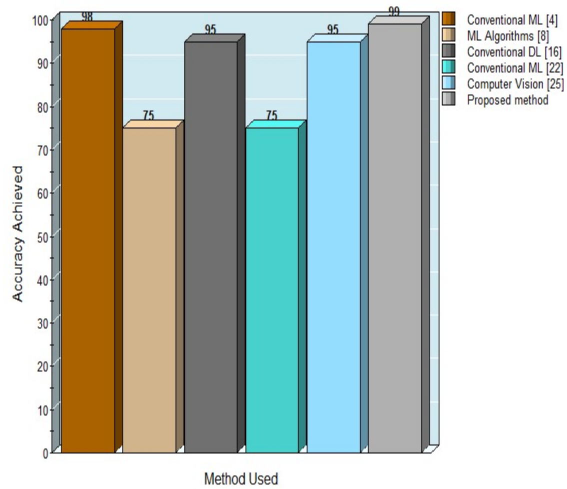


Figure 7.Proposed Method Comparison With Other Models

This paper introduced novel contributions to Autism Spectrum Disorder (ASD) detection by integrating conventional machine learning (ML) algorithms with advanced ensemble techniques across diverse age groups. Unlike prior research, which often focused on individual algorithms or specific age cohorts, this approach utilized three datasets representing adults, adolescents, and children. A novel ensemble meta-features integration technique enhanced detection performance, achieving higher accuracy. While offering advantages such as improved performance and comprehensive analysis, challenges included the complexity of ensemble techniques and the need for further optimization. Future research directions included refining ensemble techniques, integrating additional data modalities, conducting longitudinal studies, and prioritizing transparent and ethical AI solutions for ASD detection.

3.10. ASD Classification based on age groups

Building upon the ASD detection step, the analysis was extended to classify ASD cases into age-specific categories. By combining features from three separate datasets, namely Autism-Adult-Data, Autism-Adolescent-Data, and Autism-Child-Data,a unified dataset is constructed to predict ASD classification based on a range of demographic and diagnostic variables. These variables included scores from 'A1_Score' to 'A10_Score', demographic factors like 'age', 'gender', and 'ethnicity', as well as diagnostic indicators such as 'jundice' and 'austim'. Here, 'age_desc' is designated

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as the target variable, categorizing it as "18 and more" for adults, "12–16 years" for adolescents, and "4–11 years" for children. Utilizing a diverse array of ML algorithms, including logistic regression, KNN, SVM, DT, RF, AdaBoost, and gradient boosting, we achieved exceptional accuracy, exceeding 97% across all models. This comprehensive approach to ASD age specific classification underscores the efficacy of ML techniques in accurately classifying ASD across diverse age cohorts.

4. CONCLUSION

This paper proposed novel techniques for the detection of autism spectrum disorder (ASD) using a combination of conventional ML algorithms and advanced ensemble techniques. Employing three distinct age group datasetsadults, adolescents, and children, novel strategies were introduced to enhance ASD diagnosis accuracy. Through data preprocessing and analysis of top features, discriminative features for ASD detection were identified. The initial application of conventional ML algorithms established a baseline for comparison, followed by an exploration of ensemble techniques' effectiveness. The experimental findings consistently demonstrated that ensemble techniques outperformed individual models across all datasets, achieving higher accuracy, precision, recall, and F1-score. Moreover, the introduction of a novel ensemble meta-feature integration technique further enhanced performance. In addition to enhancing diagnostic accuracy, the implementation of these techniques lays a foundation for potential real-time ASD diagnosis, facilitating timely intervention and support. With the highest accuracy achieved in autism-adult data (99.2%), autism-adolescent data (99%), and autism-child data (98.7%), this research significantly advanced ML-based approaches for ASD diagnosis. Additionally, ASD classification also performed across various age groups and reported good results. These novel techniques have the potential to enhance clinical decision-making in ASD diagnosis, marking a significant step forward in addressing the challenges posed by the ASD neurodevelopmental condition.

Author Contributions

The Data collection, analysis, and implementation of machine learning algorithms were conducted by both Author 1 and Author 2. Both authors contributed to manuscript drafting and approved the final version.

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