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Autism Spectrum Disorder Diagnosis Using Machine Learning Algorithms

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ABSTRACT

The diagnosis of autism spectrum disorder (ASD) through conventional methods depends on behavioral assessments, which clinicians perform. The diagnostic process takes many clinical visits over extended periods, resulting in delayed early intervention opportunities. The therapeutic procedures that benefit patients create substantial emotional and logistical challenges for families. The research investigates how Machine Learning algorithms can improve the speed and accuracy of ASD diagnosis, creating a more efficient diagnostic process and enabling early, accessible interventions. The research evaluated three machine learning classification methods: K-nearest neighbors (KNN), stochastic gradient descent (SGD), and support vector machine (SVM). The models were trained and tested on an ASD-related feature dataset to assess their ability to identify individuals with ASD. The SGD classifier achieved the highest accuracy of 96% among the models. The high performance of ML-based diagnostic tools demonstrates their potential to improve traditional diagnostic methods by enhancing precision and efficiency. The research demonstrates that ML algorithms, specifically SGD, have strong capabilities for early and accurate ASD diagnosis. The implementation of these technologies reduces diagnostic delays and enables personalized intervention strategies, which lead to better outcomes for individuals with ASD while decreasing caregiver responsibilities.

Keywords: ASD, Diagnosis, KNN, Machine Learning, SGD, SVM.

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تشخيص اضطراب طيف التوحد بأستخدام خوارزميات التعلم الآلي

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الملخص

يعتمد تشخيص اضطراب طيف التوحد (ASD) بالطرق التقليدية على التقييمات السلوكية التي يُجريها الأطباء. تستغرق عملية التشخيص العديد من الزيارات السريرية لفترات طويلة، مما يُؤدي إلى تأخير فرص التدخل المبكر. تُشكل الإجراءات العلاجية التي تُفيد المرضى تحديات عاطفية ولوجستية كبيرة للعائلات. يبحث البحث في كيفية مساهمة خوارزميات التعلم الآلي في تحسين سرعة ودقة تشخيص اضطراب طيف التوحد، مما يُتيح عملية تشخيص أكثر كفاءة وتدخلات مبكرة سهلة المنال. قيّم البحث ثلاث طرق تصنيف للتعلم الآلي، شملت K-NN, SGD, SVM. خضعت النماذج للتدريب والاختبار من خلال مجموعة بيانات خاصة باضطراب طيف التوحد، لتحديد قدرتها على تحديد الأفراد المصابين به. حقق مُصنّف SGD أعلى معدل دقة بين النماذج، بنسبة 96%. يُظهر الأداء العالي لأدوات التشخيص القائمة على التعلم الآلي قدرتها على تحسين طرق التشخيص التقليدية من خلال تحسين الدقة والكفاءة. يُظهر البحث أن خوارزميات التعلم الآلي، وتحديدًا SGD، تمتلك قدرات قوية على تشخيص اضطراب طيف التوحد مبكرًا وبدقة. يؤدي تنفيذ هذه التقنيات إلى تقليل التأخير في التشخيص وتمكين استراتيجيات التدخل الشخصية التي تؤدي إلى نتائج أفضل للأفراد المصابين باضطراب طيف التوحد مع تقليل مسؤوليات مقدمي الرعاية.

INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex and heterogeneous neurodevelopmental condition characterized by persistent deficits in social communication and social interaction across various contexts, in addition to restricted and repetitive patterns of behavior, interests, or activities. (1). Behavioral assessments performed by trained clinicians are used because there are no objective biological markers for ASD, but they have limitations for reliable, scalable diagnostic procedures.(2, 3). Such assessments are inherently subjective and may vary considerably depending on the clinician's experience, the availability of diagnostic resources, and the cultural appropriateness of standardized instruments. (4-7). The need for diagnostic methods that are both accurate and objective, efficient and scalable is immediate. (8).

ASD typically manifests in the early developmental stages, with symptoms often observable within the first two years of life. Early diagnosis is therefore critical, as it allows for timely intervention that can positively influence cognitive, linguistic, and social outcomes. (9). Although no definitive cure currently exists for ASD, early and sustained therapeutic intervention has been shown to significantly enhance the quality of life for both individuals with ASD and their families by promoting functional development and independence. (10).

ASD encompasses a spectrum of conditions with varying degrees of severity. Asperger's Syndrome, a subtype of autism spectrum disorder, is characterized by social difficulties, nonverbal communication challenges, and repetitive behaviors, but does not impact language development or cognitive function (11). Autistic Disorder, known as classic autism, shows significant impairments in language, communication, and social interaction as well as intellectual disabilities[12]. Heller Syndrome or Childhood Disintegrative Disorder is a condition where previously acquired language, motor and social skills decline dramatically following normal development, usually along with seizure occurrence[13]. Pervasive Developmental Disorder—Not Otherwise Specified (PDD-NOS), also known as atypical autism, applies to individuals who exhibit some but not all of the core features of autism or Asperger's Syndrome [14].

In recent years, Artificial Intelligence (AI) has emerged as a promising approach for augmenting the diagnosis and treatment of ASD.[15]. Machine Learning (ML) has great potential to identify intricate patterns that enable accurate predictions of clinical outcomes.[16]. ML models can handle structured and unstructured data, such as behavioral observations, genetic information, and neuroimaging data, thereby enabling more timely and objective diagnostic decisions. [17, 18]. Previous research has applied AI in different areas of ASD, including early symptom recognition, risk evaluation and customized treatment approaches. [19, 20]. ML algorithms excel at discovering hidden relationships among high-dimensional data points, enabling them to detect direct and indirect connections and build reliable predictive models. [21]. The clinical adoption of AI systems requires extensive validation to ensure their reliability, accuracy and ethical soundness. [22].

This research extends the existing knowledge by experimentally evaluating three well-known machine learning classifiers, K-Nearest Neighbors (KNN), Stochastic Gradient Descent (SGD), and Support Vector Machine (SVM), using a well-recognized ASD dataset. This research evaluates the diagnostic potential of these algorithms to enhance traditional diagnostic approaches, making them faster, more precise and more accessible.

This paper is organized into five main sections. The first section presents the introduction, including the theoretical background and research motivation. The second section reviews the existing literature on AI-based diagnosis of ASD. The third section outlines the methodology, describing the dataset and machine learning algorithms employed. The fourth section reports and analyzes the simulation results. Finally, the fifth section concludes the study and outlines recommendations for future research.

RELATED WORK

In recent years, significant progress has been made in the classification and diagnosis of autism spectrum disorder (ASD) using machine learning (ML) and artificial intelligence (AI) techniques. From 2018 to 2025, several articles have assessed advanced computational models that would make ASD detection more accurate, efficient, and scalable. Overall classification accuracy was only 90%, and another study using ensemble-based learning on neuroimaging data found very high classification accuracy of 96.15% in functional MRI data using Random Support Vector Machine (SVM) clusters in 2018 [23]. The following year, feature reduction methods, such as the Cuckoo Search Algorithm, combined with machine learning classifiers, determined that Logistic Regression had the highest accuracy for classifying ASD across age groups [24]. In 2020, a spike in the popularity of deep learning approaches was observed. An interesting study used these approaches on resting-state fMRI data and achieved an accuracy of 85% [25]. One more hybrid architecture that combines both Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) achieved a classification accuracy of 91.2% [26]. During the same year, MRI data from AI-enhanced neuroimaging techniques enabled early detection in young children with high sensitivity and specificity [27]. In 2021, we experimented with various ML models. Their SVM model trained on brain imaging data achieved an accuracy of 88% [28]. Model accuracies of 93% were reported for early detection based on medical records, and 85% accuracy was achieved using machine learning applied to genetic data. However, a Random Forest-based model for feature selection resulted in 92% accuracy, and resting-state functional connectivity analysis together with ML techniques reached 87% accuracy [29]. Moreover, models based on behavioral data achieved 90% accuracy in Diagnosis [30].

EEG signals were integrated with machine learning techniques to reach 89% classification accuracy in 2022, and neural network models utilizing brain network features achieved 90.5% classification accuracy[31]. ASD classification accuracy with a multi-modal ML approach that integrated MRI and genetic data [32] To identify autism spectrum disorder (ASD), deep learning models trained on childhood behavioral data achieved 91% accuracy.[33]. In 2023, that trend continued, with further significant improvement. More sophisticated ML models trained on the fMRI data achieved 93% accuracy. [34]. Age and behavioral model: 92.3% accuracy. Combination cognitive and behavioral model: 94% accuracy. Deep neural networks also performed very well on MRI data, achieving up to 95% classification accuracy. [35]. Again, in 2024, another successful identification of ASD was achieved in an adult population using an AI model trained on clinical and imaging data, achieving 92% accuracy in predicting the disorder. They are a more advanced model in equipping the ability to diagnose ASD outside of a childhood population.[36].

Nonetheless, despite these very nice advances, any single methodology has inherent shortcomings. Several of the models rely on high-quality imaging or behavioral datasets that are not readily available. Some are quite large or computationally intensive, and hard to implement in low-resource settings. Additionally, many systems still struggle with generalization across heterogeneous populations and age groups.

Together, these studies reinforce the game-changing role of ML in autism research. They also emphasize the need for ongoing efforts in model refinement, multimodal data fusion, and validation across clinical contexts.

METHODOLOGY

Dataset

The Children Autism Spectrum Disorder Screening Data from the UCI Machine Learning Repository serves as the dataset for this research. The dataset provides balanced behavioral and demographic information for ASD classification by using behavioral data rather than genetic data, which currently dominates research. The dataset contains 292 instances and 21 attributes, including 10 behavioral indicators from the Autism Spectrum Quotient (AQ-10-Child) and 10 demographic and risk-related features commonly linked to ASD diagnosis. The attributes in this dataset comprise different data types (categorical, binary, and continuous) and contain missing values, making it suitable for real-world clinical classification tasks. The dataset follows DSM-5 diagnostic criteria for development and is intended for mobile-based ASD screening applications, as per Thabtah's previous research. [37-39].

The proposed model was implemented in Python. The Python libraries Pandas, NumPy and Scikit-learn were essential for data manipulation, numerical operations and model development during preprocessing. The dataset was processed to convert it to CSV format, which is available at: "Autistic Spectrum Disorder Screening Data for Children" in the UCI Machine Learning Repository.

Pre-Processing

Data preprocessing is an essential operation that improves raw data quality and consistency, enhancing machine learning model performance. The fundamental aspect of this stage involves normalization, which standardizes numerical feature scales to prevent features with larger ranges from dominating the process. [37]. The research utilizes two main normalization methods, which are:

Min-Max Scaling: This method rescales feature values to a fixed range, typically [0,1], according to the equation:

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin} \quad \ldots (1)$$

where

x is the original feature value, $x\,m\,i.n$ and $x\,m\,a.xmin$

and $xmax$ are the minimum and maximum values of the feature, respectively, and $x'$is the normalized value.

Z-score Standardization: This approach transforms feature values to have a mean of zero and a standard deviation of one, calculated as:

$$Xstd = \frac{X-\mu}{\sigma} \quad \dots (2)$$

where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ represent the mean and standard deviation of the feature[38] .

The implementation of these normalization techniques minimizes scale-dependent bias, speeds up model training and improves classification accuracy. The researchers applied Min-Max scaling and Z-score standardization to behavioral and demographic data before training machine learning classifiers for Autism Spectrum Disorder detection.[4].

Machine Learning Algorithms

Machine learning (ML) is a branch of artificial intelligence (AI) that uses algorithms to learn from data and make predictions without manual programming. [40]. Three supervised learning algorithms, namely K-Nearest Neighbors (KNN), Stochastic Gradient Descent (SGD), and Support Vector Machine (SVM), help build classification models to detect ASD. The chosen algorithms maintain a balance between interpretability, computational speed and data compatibility.

The classification system diagram in Fig. 1 illustrates the process from data preprocessing to model training and evaluation. The available data were split into training (70%) and test (30%) sets. The two subsets received normalization treatment to achieve standardized feature measurement. The training set was encoded as integers for categorical variables, but this transformation did not affect the test data to prevent information leakage. The training data were preprocessed before each algorithm received them for model building, followed by evaluation against the test data.

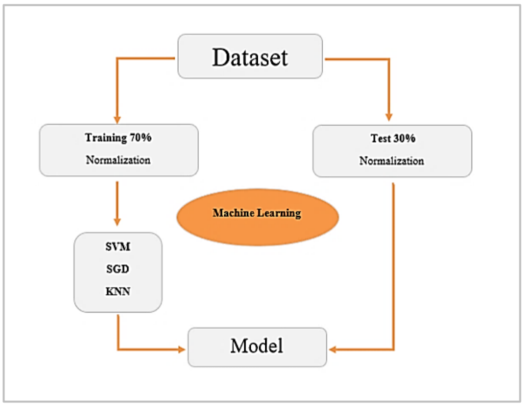

Fig. 1: The Proposed System.

K-Nearest Neighbors (KNN)

KNN is an instance-based non-parametric classifier that determines class labels by majority voting among the k nearest neighbors in the feature space. The algorithm requires two hyperparameters: k, the number of neighbors and a distance metric, which can be Euclidean or Manhattan. [41].

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + \cdots} \quad \dots (3)$$

Where d is a distance x_1, y_1 are represented as the first point x_2, y_2 are represented as the second point [42].

Stochastic Gradient Descent (SGD)

The optimization approach known as Stochastic Gradient Descent enables the training of massive machine learning models. The iterative approach of SGD differs from traditional gradient descent by using small random subsets of data (mini-batches) to update model parameters, resulting in quicker, yet noisier, convergence. [43]. The method performs best when used with convex loss functions commonly used in linear classifier applications.

$$\theta_{t+1} = \theta_t - \eta . \nabla J(\theta_t; x_i, y_i) \quad \dots (4)$$

Where θ_t represents the weight of models at the time step t, η is the learning rate, J is the loss function, and (x_i, y_i) are single training samples used in stochastic update[44].

Support Vector Machine (SVM)

SVM is a supervised learning algorithm that finds the best hyperplane to maximize the margin between classes in high-dimensional spaces. The algorithm achieves separation of non-linearly separable data by mapping the data into higher dimensions using kernel functions, where linear separation becomes feasible. [45, 46]. The decision function of SVM is expressed as:

$$f(x) = w^T x + b \quad \dots (5)$$

Where, w is the weight vector orthogonal to the hyperplane, x is the input feature vector, and b is the bias term. SVMs have proven highly effective for behavioral classification tasks, including ASD diagnosis.

Evaluation Metrics

Four standard classification metrics are used to evaluate model performance: Accuracy, Precision, Recall, and F1 Score. These metrics provide a comprehensive assessment of the classifiers' predictive abilities. [47]:

- Accuracy is the fundamental metric for a text classification model. respectively defined as:

$$Accuracy = \frac{\text{TP+TN}}{\text{N}} \quad \dots (6)$$

- precision (Pi) is the ratio of true positives to the sum of the true positives and false positives, which is the total number of predictions that were made as positive:

$$P_i = \frac{TP_i}{TP_i+FP_i} \quad \dots (7)$$

- Recall (Ri) measures the ratio of correctly predicted positive observations to all actual positive observations ():

$$R_i = \frac{TP_i}{TP_i+FN_i} \quad \dots (8)$$

- F1 Score: F1 Score is the harmonic mean of precision and recall, giving equal weight to both:

$$F1 = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP+FP+FN} \quad \dots (9)$$

Where the True Positive (TP) represents correct positive classification, while False Positive (FP) shows incorrect positive classification of negative reviews, and True Negative (TN) indicates correct negative classification, and False Negative (FN) represents positive reviews misclassified as negative.

RESULTS

Model Performance

The classification performance of three supervised machine learning algorithms—KNN, SVM, and SGD—was assessed on the test subset. The evaluation process used standard performance metrics, including accuracy, precision, recall, and F1-score. The performance results of these metrics are presented in Table 1. The accuracy of the SGD classifier reached 96%, which outperformed the SVM at 92% and the KNN at 86%.

Table 1: Results table.

Algorithms	Accuracy	Precision	Recall	F- measure
KNN	0.86	0.86	0.86	0.86
SVM	0.92	0.92	0.92	0.92
SGD	0.96	0.96	0.96	0.96

The results for precision, recall and F1-score followed the same pattern, confirming that the SGD model provided the best reliability and robustness for autism spectrum disorder (ASD) classification. These results are further visualized in Fig 2, which presents the accuracy scores for each classifier, thereby underscoring the enhanced performance of SGD for behavioral data-based ASD screening applications.

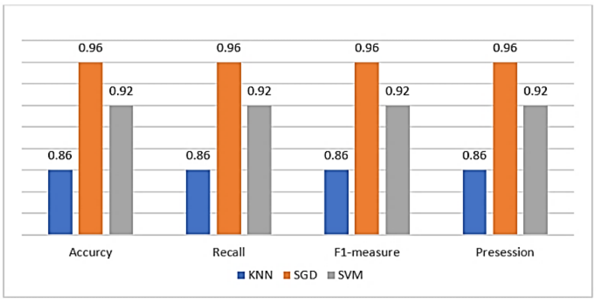

Fig. 2: Machine Learning Model Results.

Comparative Benchmarking

The evaluation of the proposed model against previous studies is presented in Table 2, which includes selected results from machine learning studies for Autism Spectrum Disorder (ASD) classification using behavioral data, neuroimaging (MRI, fMRI), and physiological signals (EEG). The analysis shows that many high-accuracy models require complex, resource-intensive data, whereas the current model achieves competitive performance with a simple, publicly available behavioral dataset. These findings show the feasibility of the proposed model, particularly in resource-limited healthcare settings and remote early screening applications, where accessibility and efficiency are critical. Table 2 provides a detailed comparison of accuracy, precision, recall, and other performance metrics between the current model and previous approaches, confirming the model's applicability across diverse environments while significantly reducing cost and time.

Table 2: Comparison with related work and Results.

Ref	Technique	Dataset	Accuracy	Precision	Recall	F-measure
(23)	Random SVM Clusters	Functional MRI	0.96	0.96	0.96	0.96
(24)	Logistic Regression + Feature Reduction	Behavioral + fMRI	0.93	0.92	0.92	0.92
(25)	Deep Learning (Resting-State fMRI)	Resting-State fMRI	0.85	0.84	0.83	0.84
(26)	Hybrid CNN RNN Model	MRI Data	0.91	0.91	0.91	0.91
(27)	AI-enhanced MRI	MRI	0.94	0.93	0.94	0.93
(28)	SVM (Brain Imaging Data)	Brain Imaging	0.88	0.87	0.87	0.87
(29)	Early Detection (ML Models)	Medical + Behavioral	0.93	0.92	0.93	0.92
(30)	Resting-State Connectivity + ML	RestingState Connectivity	0.87	0.86	0.86	0.86
(31)	EEG + Machine Learning	EEG Signals	0.89	0.88	0.88	0.88
(32)	Multi-Modal ML (MRI + Genetic)	MRI + Genetic Data	0.92	0.91	0.91	0.91
(33)	Childhood Behavioral Data + DL	Behavioral Dataset	0.91	0.91	0.91	0.91
(34)	Advanced ML on fMRI Data	fMRI	0.93	0.92	0.93	0.92
(35)	Age + Behavioral Features Model	Age + Behavioral Data	92.3	0.91	0.92	0.91
(36)	Deep Neural Networks on MRI	MRI	0.95	0.94	0.94	0.94
(37)	AI (Clinical + Imaging Data)	Clinical + Imaging Data	0.92	0.91	0.92	0.91
Our proposed system			0.96	0.96	0.96	0.96

CONCLUSIONS

The current research tackles a vital problem that exists in the medical and psychological fields regarding early and precise autism spectrum disorder (ASD) diagnosis. The complex, heterogeneous nature of ASD requires the development of reliable, objective diagnostic tools because ASD presents in multiple clinical ways. The research is of great importance because it uses machine learning methods to improve diagnostic precision, leading to earlier interventions and better patient outcomes. The research evaluated three machine learning classifiers, K-Nearest Neighbors (KNN), Stochastic Gradient Descent (SGD) and Support Vector Machine (SVM) using a normalized behavioral dataset. The assessment of model effectiveness used performance metrics, which included accuracy, precision, recall and F1-score. The SGD classifier achieved the highest accuracy of about 96% among all models. Machine learning algorithms show promise as decision-support tools that enhance traditional clinical diagnostic procedures through improved objectivity, consistency and accuracy in ASD detection. The promising research outcomes indicate that deep learning techniques should be the focus of future studies to enhance ASD classification methods. Deep learning techniques show great potential to enhance diagnostic precision and robustness because they excel at extracting hierarchical features from complex high-dimensional data. Future research should use deep learning architectures, including CNNs and RNNs, to analyze multimodal data combining neuroimaging and genetic profiles. This approach will increase diagnostic accuracy while also helping identify specific ASD subtypes to develop personalized therapeutic interventions.

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