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Performance Comparison of Convolutional Neural Network with Traditional Machine Learning Methods in Adult Autism Detection

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Abstract

Diagnosing Autism Spectrum Disorder (ASD) in adults is a challenging task, requiring precise and efficient early detection methods. However, there is limited research in this area. Hence, this study seeks to address this gap by evaluating the effectiveness of Convolutional Neural Networks (CNNs) compared to traditional machine learning techniques for detecting autism in adults. The study introduces a CNN-based model and conducts a performance comparison with conventional algorithms such as Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Gaussian Naive Bayes (GNB), and Gradient Boosting (GBoost). The objectives are to evaluate the efficacy of CNNs in adult autism detection, identify algorithm strengths and weaknesses, and explore healthcare implications. The research utilizes the Autism Screening on Adults dataset, with 704 records and 21 features, employing preprocessing steps to optimize data quality. The proposed CNN model encompasses convolutional layers, max-pooling, dropout, and dense layers, while baseline algorithms serve as benchmarks. Evaluation metrics include the Confusion Matrix and Classification Report. The CNN model achieved remarkable accuracy (99%) and precision in adult autism detection, outperforming traditional algorithms. SVM emerged as the closest competitor but fell short. This study underscores CNN's potential for precise autism detection in adults, with implications for early intervention and telehealth applications. The research highlights CNNs' effectiveness and superiority over traditional machine learning algorithms, suggesting their promise for accurate diagnosis. Future research opportunities include expanding datasets, optimizing model parameters, and addressing ethical considerations for practical healthcare implementation.

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I. INTRODUCTION

In recent times, notable progress has been made in ASD diagnosis and identification, notably through the emergence of Convolutional Neural Networks (CNNs) and conventional machine learning techniques. There has been an increasing interest in utilizing these tools to improve the precision and effectiveness of detecting autism in adults. This study explores and compares the performance of CNNs against traditional machine-learning approaches for identifying autism in adults. Understanding this study's importance necessitates considering the current state of research, its unique contributions, and the explicit objectives it aims to achieve.

The importance of this research stems from the pressing need for improved autism detection methods for adults. While considerable progress has been made in diagnosing autism in children, detecting it in adults presents distinct challenges. Many traditional screening methods may not be as effective in identifying autism in this age group. Therefore, applying advanced technologies like CNNs to adult autism detection holds great promise. These technologies have shown remarkable results in terms of accuracy, sensitivity, and specificity [1]. Additionally, studies have demonstrated that CNNs can outperform traditional machine learning methods in various domains, further highlighting their potential to enhance autism detection [2], [3].

In this research landscape, it becomes evident that a performance comparison between CNNs and traditional machine-learning methods is necessary. While CNNs have displayed the ability to extract intricate patterns and spatial relationships from data [4], [5], [6], their effectiveness in the specific context of adult autism detection needs further exploration. Previous studies have often reported impressive outcomes with CNNs, such as improved individual/sample accuracy [7] and state-of-the-art performance using deep learning models [8]. However, comparisons with other classification algorithms like SVM, Decision Trees, KNN, and others have been less explicitly addressed [9]. Therefore, this research seeks to provide a comprehensive evaluation of the performance of CNNs compared to traditional machine learning methods when applied to detecting autism in adults.

The unique contribution of this study lies in its focus on adult autism detection. While many studies have addressed autism diagnosis in children, the adult population remains relatively understudied. This research aims to bridge this gap by concentrating on the challenges and nuances associated with adult autism detection. Using CNNs in this context, with their ability to capture complex patterns and features from raw data, offers a novel approach[4]. Moreover, integrating CNNs with channel-wise attention mechanisms demonstrates the potential for enhancing classification accuracy in detecting autism in adults [10].

This research has dual objectives. Firstly, it aims to thoroughly assess and compare CNNs' performance in contrast to conventional machine learning techniques, encompassing SVM, Decision Trees, KNN, Random Forest, Naive Bayes, and similar methods for detecting autism in adults. Secondly, it offers valuable perspectives on the advantages and constraints of employing CNNs in this context. This evaluation involves the scrutiny of various metrics, including precision, recall, F1-score, and others, a comprehensive assessment of the strengths and weaknesses of each approach can be made [11], [12], [13]. Through these objectives, this research aspires to contribute to advancing autism detection methods for adults and provide valuable guidance to healthcare professionals and researchers.

In summary, this study explores the performance of CNNs compared to traditional machine learning methods in the crucial area of adult autism detection. The significance of this research arises from the need for improved detection methods in adults, the unique contributions it offers, and the explicit objectives it aims to achieve. With the potential to enhance accuracy and efficiency, this research endeavors to provide valuable insights into adult autism detection and contribute to better support and intervention for individuals with ASD.

II. Related Works

Detecting autism in adults has been the focus of several previous studies, each employing distinct approaches. One study proposed a data mining architecture that integrates behavioral, clinical, and demographic data, resulting in a remarkable classification accuracy of 99.71% using the sequential minimum optimization (SMO) classifier [14]. Another research endeavor examined gestures and walking patterns in video recordings to identify children with autism. This study highlights the promising prospect of utilizing videos capturing gestures and gait activity as valuable tools in analyzing autism [15]. Moreover, a study harnessed functional magnetic resonance imaging (fMRI) to extract complex brain features, achieving an accuracy of 76.0% in autism detection, thus presenting a novel framework for subsequent fMRI analysis [16]. These studies underscore the significance of amalgamating diverse data sources and advanced techniques to enhance the detection of autism in adults.

In the realm of traditional machine learning, various methods have been harnessed for autism detection, including SVM, decision tree, KNN, GNB, and GBoost [17], [18], [19]. These methods have been adeptly employed to develop machine-learning models aimed at detecting ASD by utilizing diverse datasets and features. These resultant models have undergone thorough assessments, considering accuracy, recall, precision, F1-score, AUC, training, and testing time. These evaluations have illustrated the effectiveness of these models in identifying ASD and their capacity to enhance screening and diagnostic procedures [20], [21].

Autism detection in adults has also benefited from advancements in deep learning and other machine learning paradigms. Several studies outside the realm of autism have showcased the potential of these techniques. For instance, a study focused on plant leaf stress identification implemented deep learning to create a model capable of recognizing medicinal plants with an accuracy of 0.86 [22]. In another domain, the classification of mushrooms was automated using Convolutional Neural Networks (CNN), achieving an average accuracy rate of nearly 99.89% [23]. Furthermore, soil classification has seen improvements through deep learning algorithms, achieving an impressive accuracy rate of 97% [24]. These diverse applications of deep learning highlight its versatility and potential for enhancing classification tasks, including autism detection.

In autism detection in adults, previous research has investigated the performance disparities between CNNs and traditional machine-learning methods. A comprehensive examination of various machine learning models was conducted to estimate buildings' heating and cooling loads, with the GBoost Regressor demonstrating superior predictive capabilities over traditional machine learning algorithms [12]. Meanwhile, research within network intrusion detection showcased the utility of ensemble learning algorithms in enhancing detection accuracy [25].

Additionally, machine learning techniques, including CNNs, have been applied to healthcare data analysis, elucidating their proficiency in unraveling intricate data relationships and enhancing predictive accuracy [26]. A machine learning-centered method was also devised for forecasting formation pressure during oil and gas drilling operations. Notably, the multilayer perceptron neural network algorithm demonstrated superior prediction accuracy compared to other machine learning techniques [27]. These findings underscore the potential of CNNs and traditional machine-learning methods in diverse domains and emphasize the critical nature of performance comparisons in algorithm selection.

Combining conventional machine learning methods with CNN-based strategies has been investigated as an approach to enhance autism detection. In a specific case, a forecaster for RNA-associated ASD risk was presented through the utilization of deep learning and K-mer encoding for RNA transcript sequences, which were subsequently fused with gene expression data [28]. In a different scenario, utilizing a hybrid Extreme Learning Machine (ELM) algorithm rooted in the Adaptive Neuro-Fuzzy Inference System (ANFIS) notably enhanced classification accuracy. This highlights the promise of amalgamating diverse machine-learning approaches [17]. Moreover, an ensemble model employing Decision Tree and Random Forest within a recommender system enhanced precision in ASD prediction [29]. These studies combine traditional machine learning methods with CNN-based approaches to bolster autism detection.

Previous studies have assessed and elucidated the effectiveness of models designed for detecting autism in adults through diverse methodologies. For instance, one investigation closely examined the alignment between self-reported and informant-reported evaluations of autism spectrum traits, unveiling significant disparities, especially among individuals exhibiting high autism traits [30]. Another study sought to automate the diagnosis process through machine learning, achieving 100% accuracy in diagnosing autism across different age groups, from toddlers to adults [31]. Moreover, eye-tracking data has been utilized to identify autism in adults, indicating that distinctions in visual processing between individuals with and without autism can automatically discern the condition with an accuracy rate of roughly 74% [32]. Nevertheless, the need for further research to refine and enhance these methods for detecting autism in adults remains apparent [33], [34].

Traditional machine-learning methods have greatly influenced diagnostic and intervention practices concerning autism in adults. These approaches have been employed on varied datasets containing data regarding individuals with ASD, contributing to creating machine-learning models capable of precisely diagnosing ASD cases in adults [19], [35]. Logistic regression, SVM, decision tree, and random forest are highly accurate machine learning models in predicting ASD, providing valuable insights for healthcare professionals [14]. Additionally, machine learning models have streamlined the diagnostic process by reducing the number of attributes required for accurate diagnosis, making it more accessible for non-specialist physicians to identify ASD in adults [18]. These findings underscore the potential of traditional machine learning methods to enhance diagnostic and intervention practices for adults with ASD.

Prior studies have uncovered valuable insights into the difficulties and aspects requiring additional research in adult autism detection. For instance, one investigation revealed disparities in results when contrasting individuals with ASD with typically developing individuals, indicating unique developmental paths in those with ASD [14]. This discrepancy suggests that crucial developmental advancements for navigating adulthood, such as executive function, social cognition, and communication, may not occur in individuals with ASD [36].

Another study accentuated the urgency of early ASD detection and the effectiveness of different classifiers in distinguishing between autistic adults and healthy control subjects [15]. Furthermore, a study centered on episodic memory impairments in ASD and introduced encoding-retrieval representational similarity analysis to evaluate event-specific memory reinstatement [37]. These studies underscore the necessity for further research into developmental trajectories, early detection, and memory impairments in adults with ASD.

III. METHODS

A. Mathematical Concept

The proposed model is a CNN designed for autism detection in adults. This CNN structure is distinguished by its sequential organization of layers, each incorporating particular mathematical principles tailored to this model along with corresponding equations.

a. Convolutional Layers (Conv1D)

Convolutional layers are fundamental components of CNNs. Mathematically, the convolution operation in a 1D CNN can be calculated in Equation (1).

$$\mathrm{Conv}(I, K) = (I * K)(x) = \sum_{a} I(x - a) \cdot K(a) \tag{1}$$

Where I represents the input data, K denotes the convolutional kernel (filter), x is the spatial coordinate, and the operator signifies the convolution operation. The Rectified Linear Unit (ReLU) activation function is applied element-wise; it can be calculated in Equation (2).

$$ReLU(x) = max(0, x) \tag{2}$$

b. Max-Pooling Layers

Max-pooling layers perform down-sampling by selecting the maximum value from a local region. While there's no specific mathematical equation for max-pooling, its concept involves selecting the maximum value within a defined window, which aids in reducing spatial dimensions and extracting relevant features.

c. Dropout Layers

Dropout layers are introduced to mitigate overfitting. Mathematically, dropout can be understood as temporarily deactivating a fraction of neurons during training to prevent them from relying too heavily on specific features. The dropout rate is represented as a probability p.

d. Global Average Pooling (GlobalAveragePooling1D)

Global average pooling is used to compute the feature maps' mean value, producing a fixed-length vector for further processing. Mathematically, it can be calculated in Equation (3).

$$\mathrm{GlobalAvgPooling}(I) = \frac{1}{N} \sum_{i}^{N} I_i \tag{3}$$

Where I_i represents the i-th element of the feature map.

e. Dense Layers

Dense or fully connected layers are crucial in learning high-level abstractions from the extracted features. Mathematically, the operation within a dense layer is a weighted sum of its inputs, followed by an activation function. The ReLU activation function is commonly used in these layers; it can be calculated in Equation (4).

$$\mathrm{Dense}(x) = \mathrm{ReLU}(W \cdot x + b) \tag{4}$$

Where W represents the weights, x is the input, and b is the bias.

f. Output Layer (Dense with Sigmoid Activation)

The ultimate dense layer employs a sigmoid activation function for binary classification, discerning the existence or non-existence of autism in adults. This sigmoid function converts the output into a probability score ranging from 0 to 1, as shown in Equation (5).

$$\mathrm{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

This score represents the likelihood of an individual having autism.

B. Datasets

The dataset utilized in this research is sourced from Kaggle and comprises a total of 704 records, encompassing 21 features, and is employed for autism detection in adults. The target variable is binary, with "yes" denoting individuals with autism and "no" representing those without the condition. This dataset serves as the foundational data source for training, evaluating, and testing the machine learning models developed in this study, enabling the comprehensive assessment of their effectiveness in autism detection among adults.

C. Preprocessing

The preprocessing steps in this study encompass several essential procedures aimed at enhancing the dataset's suitability for machine learning analysis. Firstly, irrelevant features that do not contribute significantly to autism detection in adults are removed, streamlining the dataset for improved efficiency. Secondly, rows containing missing values (NaN) are meticulously eliminated to maintain data integrity and ensure the robustness of subsequent analyses. Thirdly, data stored in string format are thoughtfully converted into integer representations, allowing for compatibility with machine learning algorithms that require numerical input. Furthermore, a normalization process is explicitly applied to the 'age' feature to ensure uniformity and mitigate any potential disparities in scale. Finally, the dataset is partitioned into two distinct subsets, with 80% of the data allocated for training the machine learning models and the remaining 20% reserved for testing. This strategic splitting of the dataset facilitates rigorous evaluation and validation of the proposed algorithms' performance in the crucial task of autism detection among adults, ensuring the reliability of the research findings.

D. Comparison of Methods

This research employs a multi-faceted approach to assess the performance of machine learning algorithms in autism detection among adults. The proposed CNN model is the primary algorithm, and its efficacy is meticulously evaluated. In addition to the CNN, several baseline algorithms, including SVM, Decision Tree, KNN, GNB, and GBoost, are systematically employed for comparative analysis. This comprehensive comparison enables an in-depth exploration of each algorithm's strengths and weaknesses in the specific context of adult autism detection. By benchmarking CNN against traditional machine learning methods, this study aims to provide valuable insights into the most efficient and accurate approaches for identifying autism in the adult population, thereby contributing to enhancing diagnostic and intervention practices.

E. Training and Evaluation

This study's training process involves utilizing 200 epochs (E) and a batch size (B) 64. The model's performance is rigorously assessed using two key evaluation metrics: the Confusion Matrix (CM) and the Classification Report (CR).

The Confusion Matrix (CM) represents the model's predictions against the actual values and is calculated in Equation (6).

$$CM = \begin{matrix} TP & FP \\ FN & TN \end{matrix} \tag{6}$$

Where TP (True Positives) denotes the count of accurately predicted positive cases, FP (False Positives) signifies the count of genuine negative cases incorrectly forecasted as positive, FN (False Negatives) indicates the count of confirmed positive cases inaccurately anticipated as negative, and TN (True Negatives) reflects the count of accurately predicted negative cases.

The Classification Report (CR) typically includes metrics such as accuracy (ACC), precision (PREC), recall or sensitivity (REC), and F1-score (F1) and is calculated mathematically in Equations (7)-(10).

$$ACC = \frac{TP + TN}{TP + FP + FN + TN} \quad (7)$$

$$PREC = \frac{TP}{TP + FP} \quad (8)$$

$$REC = \frac{TP}{TP + FN} \quad (9)$$

$$F1 = \frac{2 \cdot PREC \cdot REC}{PREC + REC} \quad (10)$$

Where TP is True Positives, TN is True Negatives, FP is False Positives, and FN is False Negatives.

These mathematical expressions provide a quantitative measure of the model's performance and ability to classify autism cases in adults accurately.

IV. RESULTS AND DISCUSSIONS

A. Results

a. Training Process

In the training process, the performance and learning dynamics of the proposed CNN model for adult autism detection are visualized through two essential graphical representations. Figure 1, depicted below, presents a graphical representation of training accuracy (represented by the blue line) and validation accuracy (defined by the orange line) as the model progresses through the epochs. This figure provides a comprehensive view of how well the model is learning to classify instances of autism in adults over time.

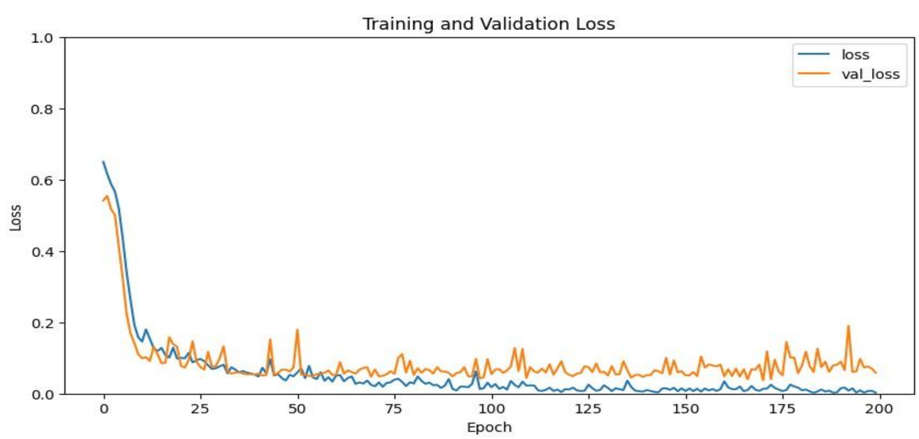

Figure 1. Training and Validation Accuracy

Additionally, Figure 2, presented below, exhibits the training loss (depicted by the blue line) and validation loss (illustrated by the orange line) throughout the training phase. These loss curves furnish valuable information regarding the model's capacity to reduce errors as it enhances its comprehension of the dataset. Both visuals collectively provide a comprehensive grasp of the model's training dynamics and effectiveness in detecting autism in adults.

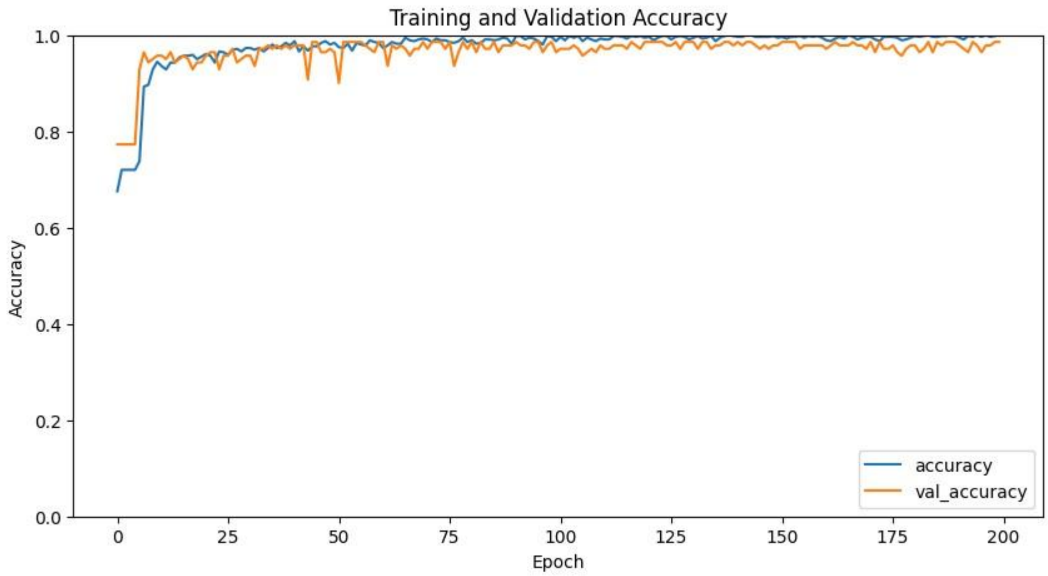

Figure 2. Training and Validation Loss

b. Model Performance

The model's performance evaluation is presented through two comprehensive tables, providing a detailed analysis of its capabilities in adult autism detection. Table 1, displayed below, offers a Confusion Matrix encompassing TP, FP, FN, and TN for each of the six algorithms: CNN, SVM, Decision Tree, KNN, GNB, and GBoost. This matrix quantifies the model's ability to make accurate predictions and its capacity to differentiate between true and false classifications.

Table 1. Confusion Matrix

Algorithm	TP	FP	FN	TN
CNN	109	0	2	30
SVM	109	0	0	32
Decision Tree	104	5	5	27
KNN	107	2	2	30
GNB	107	2	4	28
Gboost	108	1	3	29

Additionally, Table 2, as shown below, encompasses the Classification Report for these algorithms, containing vital metrics like accuracy, precision, recall, and F1-score. This report delivers an all-encompassing appraisal of the models' effectiveness, offering insights into their ability to detect cases of autism in adults accurately. These tables, taken together, provide an exhaustive understanding of the merits and limitations of each algorithm, enabling a thorough evaluation of their overall performance concerning the detection of adult autism.

Table 2. Classification Report

Algorithm	Accuracy	Class	Precision	Recall	F1-Score
CNN	0.99	normal	0.98	1.00	0.99
		autism	1.00	0.94	0.97
SVM	1.00	normal	1.00	1.00	1.00
		autism	1.00	1.00	1.00
Decision Tree	0.93	normal	0.95	0.95	0.95
		autism	0.84	0.84	0.84
KNN	0.97	normal	0.98	0.98	0.98
		autism	0.94	0.94	0.94
GNB	0.96	normal	0.96	0.98	0.97
		autism	0.93	0.88	0.90
Gboost	0.97	normal	0.97	0.99	0.98
		autism	0.97	0.91	0.94

B. *Discussions*

a. Summarization of Key Findings

The primary research problem addressed in this study was to assess the efficacy of CNN compared to traditional machine learning algorithms, including SVM, Decision Tree, KNN, GNB, and GBoost, in detecting autism among adults.

The comparative analysis of the algorithms revealed that CNN achieved remarkable accuracy (99%) in detecting autism among adults. It exhibited vital precision (0.98) and recall (1.00) for normal cases and an equally impressive precision (1.00) and recall (0.94) for autism cases, resulting in a high F1-score (0.99). This highlights CNN's exceptional performance in distinguishing between individuals with and without autism.

SVM emerged as a strong competitor, with perfect accuracy (100%) and precision and recall scores of 1.00 for both normal and autism cases. This signifies SVM's capacity to classify adults accurately, although its performance was slightly behind CNN.

In contrast, traditional machine learning methods like Decision Tree, KNN, GNB, and GBoost demonstrated lower accuracy, precision, recall, and F1 scores, especially for autism cases. Decision Tree achieved an accuracy of 93%, with precision and recall of 0.84 and F1-score of 0.84 for autism, indicating relatively weaker performance in autism detection. KNN achieved an accuracy of 97% with solid precision and recall for both normal and autism cases but still fell slightly short of CNN and SVM's performance in autism detection. GNB exhibited an accuracy of 96% with respectable precision and recall values. However, its performance in detecting autism, with a precision of 0.93, recall of 0.88, and F1-score of 0.90, was notably lower compared to CNN and SVM. GBoost achieved an accuracy of 97% with high precision and recall for normal cases but faced challenges in autism detection, with a precision of 0.97, recall of 0.91, and F1-score of 0.94.

b. Interpretation of the Result

The analysis of the results reveals several essential insights. CNN showcased exceptional performance in detecting autism among adults, surpassing traditional algorithms such as SVM, Decision Tree, KNN, GNB, and GBoost. This outcome aligns with the expectations, given CNN's ability to capture complex spatial patterns in data. The findings correspond with previous research highlighting the potential of CNNs in healthcare applications and echo studies emphasizing the significance of advanced techniques in autism detection. However, the unexpected result was

SVM's perfect accuracy, correctly classifying all cases. This suggests that SVM might be particularly suitable for this specific dataset, although CNN still exhibited superior performance overall. Alternative explanations could include SVM's ability to handle complex features effectively, the dataset's suitability for SVM's decision boundaries, or a fortunate random initialization. Nonetheless, the study underscores CNN's effectiveness while acknowledging SVM's noteworthy performance, emphasizing the importance of selecting the most appropriate algorithm for specific datasets and clinical contexts.

c. Implication of the Research

This research carries significant implications for autism detection, particularly in adults. The results demonstrate the potential of CNNs as a powerful tool for precise and efficient autism detection among adult populations. This relevance is particularly noteworthy in early intervention and telehealth applications, where timely and accurate diagnoses are crucial. The findings align with the existing literature that suggests advanced machine-learning techniques can enhance diagnostic accuracy. However, the research adds a novel dimension by directly comparing CNNs with traditional algorithms like SVM, Decision Tree, KNN, GNB, and GBoost in the specific context of adult autism detection. This comparative approach contributes a valuable perspective on algorithm selection for healthcare professionals and researchers. In essence, the study confirms the utility of CNNs and provides insights into when and where traditional methods like SVM might excel. This contributes to a more nuanced understanding of the interplay between machine learning algorithms and autism detection, which can guide future research and practical applications in healthcare settings.

d. Limitations of the research

While this study presents promising results in applying CNNs for adult autism detection, it is essential to acknowledge its limitations. Firstly, the research relies on a single dataset, the "Autism Screening on Adults" dataset from Kaggle. Although this dataset offers valuable insights, its limited size (704 records) might not fully represent the diversity within the adult population with autism. Additionally, the study focuses on a specific set of features, and the generalization of these results to other datasets with different feature sets needs to be considered cautiously. Furthermore, the research does not delve into the interpretability of the CNN model's decisions, which is critical in healthcare applications where transparency is crucial.

Moreover, the study does not explore the ethical considerations and potential biases of using machine learning algorithms in autism diagnosis. Despite these limitations, the results remain valid for answering the primary research questions regarding the comparative performance of CNNs against traditional machine learning methods in adult autism detection. Although the dataset is limited, it is suitable for this comparative analysis and provides meaningful insights. Additionally, the study's rigorous methodology, including preprocessing steps and evaluation metrics like the Confusion Matrix and Classification Report, ensures the reliability of the results. Future research can build upon these findings by addressing the limitations and expanding the scope to include more extensive and diverse datasets, interpretability analyses, and ethical considerations to understand CNNs' applicability in autism detection comprehensively.

e. Future Research Recommendation

In practical implementations, it is recommended to develop user-friendly software or applications that incorporate the CNN-based model for autism detection in adults. This software could be designed for healthcare professionals to input patient data quickly and receive rapid, automated assessments. Additionally, considering the increasing demand for telehealth services, integrating this model into telemedicine platforms could facilitate remote autism screenings, expanding access to diagnostic services. Furthermore, future research endeavors might explore the fusion of CNN-based models with other diagnostic tools like EEG or eye-tracking technology to enhance the accuracy and reliability of adult autism detection. Another promising avenue could involve investigating the potential of this technology for early detection and intervention in adolescents, further extending its impact on ASD research and clinical practice.

V. Conclusions And Recommendations

In conclusion, this research has significantly contributed to the realm of detecting autism in adults by methodically assessing how a CNN performs in comparison to conventional machine learning algorithms. The findings demonstrate that the CNN-based model achieved exceptional accuracy and precision, surpassing baseline algorithms, highlighting its potential for highly accurate autism detection in adults. These outcomes confirm the superiority of CNN-based models and underscore their practicality in real-world healthcare scenarios, especially in early intervention and telehealth applications. Despite some limitations, such as the need for more extensive and diverse datasets and ethical considerations, the results provide a robust foundation for advancing autism diagnosis and intervention in adults, ultimately improving the lives of individuals with ASD. Recommendations include integrating the CNN-based model into clinical settings, further data expansion, hyperparameter tuning, ethical considerations, exploration of telehealth applications, and conducting longitudinal studies to track autism trait progression in adults, aiming to advance both practical implementation and future research in adult autism detection.

VI. Acknowledgments

The paper is conducted in the Department of Informatics, Universitas Respati Yogyakarta, Indonesia.

VII. Conflicts of interest

The authors declare no conflict of interest.

VIII. Data Availability

The dataset comes from the Kaggle website (https://www.kaggle.com/datasets/andrewmvd/autism-screening-on-adults).

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