A Comparative Study of Machine Learning Approaches for Autism Detection in Children from Imaging Data

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Abstract
Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects language, communication, cognitive, and social skills. Early detection of ASD in children is crucial for effective intervention, and machine learning techniques have emerged as promising tools to improve the accuracy and efficiency of detection. This paper presents a range of Machine Learning approaches that have been applied to identify individuals with ASD, with a particular focus on children, using images as input data. The results of these studies demonstrate the potential for Machine Learning to aid in the early detection and diagnosis of ASD in children, which can lead to better outcomes for individuals with this condition.

Keywords
Autism Spectrum Disorder (ASD), Machine Learning, Convolutional Neural Network

1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that affects social interaction, communication, and behavior. It is called a "spectrum" disorder because the symptoms and severity can vary widely between individuals, ranging from mild to severe. Some people with ASD may have exceptional abilities in areas such as music, art, or math. The exact causes of ASD are not yet fully understood, but it is believed to be a complex interaction between genetic and environmental factors. There is also no known cure for ASD, but early intervention and treatment can help to improve outcomes for individuals with the disorder. The symptoms of ASD typically appear in early childhood and may include: difficulties with social interaction and communication, such as avoiding eye contact, not responding to their name, or having difficulty understanding nonverbal cues like facial expressions or body language; repetitive behaviors or routines, such as repeating words or phrases, lining up toys or objects, or becoming upset with changes in routine; sensory sensitivities, such as being overly sensitive to certain textures, sounds, or lights; restricted interests, such as having an intense focus on a particular topic or activity, or becoming upset if a particular interest is interrupted. Diagnosis of ASD typically involves a comprehensive evaluation by a team of professionals, including a pediatrician, psychologist, and other specialists. Early diagnosis and intervention, such as behavioral therapy and support services, can help to improve outcomes and enhance the quality of life for individuals with ASD. Diagnosing Autism Spectrum Disorder (ASD) typically involves a comprehensive evaluation by a team of professionals, including a pediatrician, psychologist, and other specialists. There is no single test that can diagnose ASD, and the diagnostic process typically involves a combination of medical and developmental assessments, behavioral evaluations, and interviews with parents or caregivers. Some of the common tests and evaluations that may be used in the diagnostic process for ASD include: Developmental and behavioral screenings, brief tests that assess a child's development and behavior, such as the Modified Checklist for Autism in Toddlers (M-CHAT), which is often used for children aged 16 to 30 months; Comprehensive diagnostic evaluation, this typically involves a more in-depth assessment of a child's development, behavior, and communication, including a review of medical and family history, interviews with parents or caregivers, and observation of the child's behavior; Autism Diagnostic Observation Schedule (ADOS), a standardized assessment tool that uses structured activities and observations to evaluate communication, social interaction, play, and restricted or repetitive behaviors; Autism Diagnostic Interview-Revised (ADI-R), a structured interview with parents or caregivers that covers a range of topics related to a child's development and behavior, including language skills, social interaction, and repetitive behaviors; Medical and genetic testing to rule out other medical conditions or genetic disorders

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that may have similar symptoms to ASD. The incidence of ASD traits attributed to genetic factors is estimated around 81% of the population, moreover environmental factors have been associated in literature with about 14% to 22% of the risk of ASD[1], while genetic risk factors for ASD overlap with other diverse developmental and psychiatric disorders [2, 3] However a relatively small number of rare genetic variants (approximately 100 genes) have been identified that were associated with a significant risk [**?** 3] along with the advancement of the risk factor correlated with paternal age [4, 5, 6, 7, 8].

It's important to note that the diagnostic process for ASD can be complex and may require multiple evaluations over time. Additionally, not all individuals with ASD may be diagnosed in early childhood, and some may receive a diagnosis later in life. Autism, also known as Autism Spectrum Disorder (ASD), is a neurodevelopmental disorder that affects how people interact with others, communicate, learn, and behave.
Autism is a complex and lifelong condition that is typically diagnosed in early childhood. Individuals with autism may have difficulty with verbal and nonverbal communication, such as making eye contact, using facial expressions, and understanding body language. They may also struggle to initiate and maintain social relationships, have difficulty with imaginative play, and show repetitive and restrictive behaviors.
Autism is a spectrum disorder, meaning that it affects individuals differently, and each person with autism has a unique set of strengths and challenges. Some individuals with autism may have exceptional abilities in areas such as mathematics, music, or art, while others may have difficulty with daily living skills such as dressing and grooming. The causes of autism are not fully understood, but research suggests that a combination of genetic and environmental factors may contribute to the development of the disorder. There is currently no cure for autism, but early intervention and appropriate educational and therapeutic support can help individuals with autism reach their full potential and lead fulfilling lives. A proper autism treatment may entail a number of interventions such as behavior therapy, occupational therapy, and talk therapy. Furthermore, it is critical that the child obtains an education that is tailored to his needs, with teachers who are appropriately prepared to work with autistic children. Parents play an important role in assisting their autistic children in coping with daily obstacles. This could include establishing routines and soothing locations, encouraging communication and socializing, and actively participating in their child's therapy and school curricula. It's important to note that autism is not a mental illness or intellectual disability, and individuals with autism should not be defined solely by their diagnosis. Computer-based methods are becoming increasingly important for detecting autism in young children. Common methods for autism detection include cognitive tests, questionnaires based on autism symptoms, video recording analysis, social interaction analysis, and brain scanning. Cognitive tests can be used to evaluate memory, visual perception, reasoning, and problem-solving skills in children, which may be affected if they are autistic. Questionnaires based on autism symptoms are often used to assess the presence of typical autism behaviors, such as repetitive behaviors and difficulty with social communication, in young children. Video recording analysis can provide insights into social communication skills and behavior patterns, and can be used to identify potential indicators of autism in young children. Social interaction analysis involves observing the interactions between young children and their caregivers or peers and can provide information on the child's social communication abilities and potential indicators of autism. Finally, brain scanning techniques such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) can provide insights into the neural mechanisms underlying autism and may be used to identify early indicators of the disorder. There are also methods based on machine learning (ML) that can analyze large amounts of data and identify patterns that may be difficult to detect using traditional methods [9, 10, 11]. They can also provide objective assessments of autism symptoms and improve accuracy. Recent studies have explored the use of ML for early autism detection, including the analysis of eye-tracking data and brain activity patterns [12, 13]. These studies have shown promising results, suggesting that ML methods may be effective tools for improving autism detection and facilitating early intervention in young children. Overall, the use of ML in autism detection represents an exciting area of research, with the potential to significantly improve our understanding of autism and lead to more effective interventions for children with the disorder.

2. Related Works

Machine learning techniques have been used in recent years to help diagnose, predict and improve treatment for autism spectrum disorder (ASD). While there is still much to learn and discover about this complex neurodevelopmental disorder, researchers are making progress in applying machine learning algorithms to ASD.

Some of the current state-of-the-art machine learning approaches for ASD include: Deep learning models, neural network models that are capable of learning and extracting complex patterns from large and heterogeneous datasets. Deep learning models have been used for early detection of autism, predicting treatment outcomes, and understanding the neurobiological basis of the disorder; Support Vector Machines (SVM), a machine learning algorithm that is commonly used in classification problems. SVMs have been used to classify autistic and non-autistic individuals based on their brain connectivity patterns, facial expressions, and speech patterns; Random Forests, an ensemble learning algorithm that combines multiple decision trees to make predictions. This approach has been used to identify genetic markers that are associated with autism and to predict the severity of autism symptoms.; Natural Language Processing (NLP), a field of study that focuses on the interactions between computers and human languages. NLP has been used to analyze language patterns in individuals with autism, including their use of pronouns, repetition, and lexical diversity; Transfer Learning; a technique that involves training a machine learning model on a large dataset and then transferring the learned features to a smaller dataset. Transfer learning has been used to develop models for early detection of autism using electroencephalography (EEG) data. Overall, machine learning approaches hold great promise for improving the understanding, diagnosis, and treatment of autism spectrum disorder. However, further research is needed to ensure that these techniques are reliable, valid, and scalable in real-world settings. Several analyzes of ML methods for disease detection are recently proposed. In 2015 machine learning algorithms were used [14]to evaluate the Autism Diagnostic Observation Schedule (ADOS) to determine if a subset of behaviors can effectively differentiate between children with and without autism spectrum disorder (ASD). The study found that only a few behaviors are sufficient to detect ASD risk with high accuracy. The results suggest that computational and statistical methods can help streamline ASD risk detection and screening, potentially enabling the development of mobile and parent-directed methods for preliminary risk evaluation and clinical triage. Other ML and cloud-based approaches are still under study for remote assesment, follow up and therapeutic support, also for ASD-affected children [15, 16, 17, 18, 19, 20, 21]

Regarding the choice of characteristic features that should be mentioned Vaishali et al. [22] discuss the use of machine learning-based behavioral analytics for detecting the risk of autism. The study experiments with a dataset of 21 features obtained from the UCI machine learning repository using a swarm intelligence-based binary firefly feature selection wrapper. The experiment finds that 10 features are sufficient to distinguish between ASD and non-ASD patients and achieve an average accuracy range of 92.12%-97.95% with the optimum feature subset, which is comparable to the accuracy produced by the entire ASD diagnosis dataset.

Another study by Thabtah et al. [23] proposed a new machine learning technique called Rules-Machine Learning (RML) that offers a knowledge base of rules to understand the underlying reasons behind the classification of autism spectrum disorder (ASD) traits. The RML model achieved an error rate of less than 5.6%, but the dataset used was unbalanced concerning class labels, with 515 cases belonging to NO-ASD and only 189 cases with ASD.

Furthermore, Z Sherkatghanad et al. [24] proposed a model based on Convolutional Neural Network that can detect ASD correctly with an accuracy of 70.22% using the ABIDE I dataset and the CC400 functional parcellation atlas of the brain.

3. Implementation

In this research project, we have employed different machine learning models to classify subjects either as having ASD (autism spectrum disorder) or not. The performance of each classifier was then evaluated to identify the best model.

3.1. Dataset

The Dataset [25] used in this study included 3,014 facial images of children with autism and typically developing children, sourced from the publicly accessible Kaggle platform. Half of the images were of children with autism, while the other half were of non-autistic children. The images were collected through various online sources, including websites and Facebook pages dedicated to autism. The creator of the dataset automatically cropped the face from the original images and already divided the dataset into train, validation, and test subparts, as shown below (Table 1).

Table 1
Splitting of the dataset for training, testing, and validation.

Total images	Training set	Validation set	Testing set
3,014	2,654	80	280

3.2. Machine Learning methods

We used a variety of classification algorithms from Scikit-learn, a popular Python Machine Learning library. The algorithms used include Decision Tree, Random Forest, Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN).

3.2.1. Decision Tree

Decision Trees are a type of non-parametric supervised learning method that is used for classification and regression. The goal is to build a model that predicts the value of a target variable using simple decision rules derived from data features. A tree is an example of a piecewise constant approximation. A decision tree is a type of machine learning algorithm that is used for classification and regression analysis. It is a graphical representation of all possible solutions to a decision based on certain conditions or input variables. In other words, a decision tree is a tree-like structure that represents a set of decisions and their possible consequences. In a decision tree, each node represents a decision point based on a certain feature or attribute. The branches that emanate from the node represent the possible outcomes or choices that can be made based on the decision point. At each subsequent node, the algorithm evaluates the available options and makes a decision based on the best available information. For example, suppose we are trying to predict whether a person will purchase a product based on their age and income. The decision tree algorithm would first split the data based on age into two groups: those under a certain age and those over it. The algorithm would then evaluate the income of each group and determine which group is more likely to purchase the product based on that criterion. The algorithm would then split that group further based on other available features or attributes and continue to evaluate and split the data until a final decision is reached. Decision trees can be useful for a variety of machine learning tasks, such as prediction, classification, and feature selection. They are often used in decision support systems, customer segmentation, and marketing analytics.

3.2.2. Random Forest Classifier

This is a learning method that can be used for classification as well as regression. It works in the context of image classification by constructing multiple decision trees, each of which employs a subset of the features and samples. The final prediction is then made by aggregating all of the trees' predictions. A Random Forest is a machine learning algorithm that is based on decision trees. It is an ensemble learning method that combines multiple decision trees to make a more accurate prediction. The algorithm works by creating a large number of decision trees, each of which is trained on a different subset of the data and a random subset of the available features. The algorithm then combines the predictions of each tree to arrive at a final prediction. Random Forests are known for their high accuracy and robustness against overfitting, a common problem in decision trees. By using multiple decision trees and aggregating their predictions, a Random Forest is able to reduce the impact of individual trees that may be overfitting the data. Additionally, the random selection of features at each node helps to increase the diversity of the trees and reduce correlation between them, further reducing the risk of overfitting. The Random Forest algorithm can be used for both classification and regression problems. In a classification problem, the algorithm predicts the class or category of a sample based on a set of input features. In a regression problem, the algorithm predicts a continuous output variable based on a set of input features. Random Forests are commonly used in a variety of applications, such as image classification, customer churn prediction, and financial forecasting. They are particularly useful when dealing with large and complex datasets, where traditional statistical methods may not be sufficient.

3.2.3. Support Vector Machine (SVM)

SVM is an algorithm for classification tasks that works by finding the optimal hyperplane that separates the data points of different classes. In image classification, SVM can be used to separate the different classes of images based on their feature values. A Support Vector Machine (SVM) is a type of machine learning algorithm used for classification and regression analysis. SVMs are based on the concept of finding a hyperplane that best separates data into different classes. In other words, an SVM tries to find the best possible boundary that separates different classes of data, such that the distance between the boundary and the closest data points (known as support vectors) is maximized. The SVM algorithm works by first mapping the input data to a high-dimensional feature space, where it becomes easier to separate the different classes. The algorithm then finds the hyperplane that maximizes the margin between the support vectors of the different classes. The margin is the distance between the hyperplane and the closest data points, and the support vectors are the data points that are closest to the hyperplane. SVMs can be used for both linear and nonlinear classification and regression problems. In linear SVMs, the data can be separated using a straight line or a hyperplane, while in nonlinear SVMs, the data can be separated using more complex curves or surfaces. SVMs are popular in machine learning because they have a strong theoretical foundation and have been shown to perform well on a variety of datasets. They are particularly useful when dealing with datasets that have a large number of features, as SVMs can handle high-dimensional data with relative ease. SVMs have been used in a wide range of applications, including text classification, image classification, and bioinformatics.

3.2.4. k-Nearest Neighbors

K-Nearest Neighbor (kNN) is a supervised classification algorithm used for predicting the class of a new data point. The basic idea behind kNN is to find the k closest data points in the training set to the new data point and assign the most common class among these neighbors to the new one. k-Nearest Neighbors (k-NN) is a machine learning algorithm used for classification and regression analysis. The algorithm works by finding the k data points in the training set that are closest to a given data point in the test set, and then using the labels of these nearest neighbors to make a prediction for the test point. In k-NN classification, the algorithm predicts the class of a test sample by identifying the k nearest neighbors in the training set and assigning the class that is most common among them to the test sample. The value of k is usually chosen by the user and can be a hyperparameter tuned through cross-validation. In k-NN regression, the algorithm predicts the value of a continuous variable for a test sample by identifying the k nearest neighbors in the training set and taking the average (or weighted average) of their values. The k-NN algorithm is simple and easy to understand, and can be applied to a variety of problems with different types of data. However, it can be computationally expensive, especially when the training set is large. Additionally, k-NN can be sensitive to the choice of distance metric used to measure the similarity between data points. k-NN has been used in a wide range of applications, including image recognition, recommendation systems, and anomaly detection. It is particularly useful when the underlying distribution of the data is not well known or when the decision boundary is complex and nonlinear.

3.2.5. Results

Below are the results obtained from the different machine learning methods (Table 2).

Classifier	Accuracy	Precision	Recall	F1-score
Decision Trees	0.657	0.664	0.636	0.650
Random Forests	0.800	0.792	0.814	0.803
k-Nearest Neighbors	0.718	0.877	0.507	0.643
Support Vector Machines	0.764	0.785	0.729	0.756

Table 2
Results of Machine Learning Methods

The outcomes demonstrate that the Random Forests classifier outperforms the others in terms of performance. Notably, Random Forests have attained the highest F1-score, accuracy, and precision. On the other hand, k-Nearest Neighbors had the highest precision but the lowest recall. The fact that k-Nearest Neighbors is more sensitive to noise and outliers in the data may cause its low recall. On the other hand, Support Vector Machines had the highest recall but relatively lower precision. This suggests that SVMs are more effective at identifying positive and negative samples. Regarding precision and recall, Random Forests and Support Vector Machines have demonstrated balanced performance, indicating that they can handle unbalanced datasets.

3.3. Convolutional Neural Network

We also implemented a Convolutional Neural Network (CNN) to classify images. CNNs have been shown to be extremely effective at image recognition tasks and to be able of learning complex features from images. We trained and evaluated the CNN on the same dataset that we used to train and evaluate the other Machine Learning algorithms, and we compared its performance to the other methods. With the addition of a CNN, we can investigate the advantages and disadvantages of using deep learning methods for autism detection.

3.3.1. Architecture

Our Convolutional Neural Network (CNN) consists of an input layer with images of size 224x224 and 3 RGB channels. It has 7 convolutional layers with 64 filters of size 3x3 and ReLU activation function. Batch normalization layers follow each convolutional layer to normalize the output of feature maps. Max pooling layers of size 2x2 reduce the dimension of feature maps and preserve salient features. The final Max Pooling Layer is followed by a Flatten Layer that converts the feature map into a one-dimensional vector. The network has two fully connected layers with 128 units and ReLU activation function in the first layer, and a single unit with a sigmoid activation function in the output layer. A Dropout Layer with a dropout rate of 50% is added between the fully connected layers to prevent overfitting. The output layer has a single unit with a sigmoid activation function. The model is compiled with binary cross-entropy loss, Adam optimizer, and accuracy as the metric.

The model is trained for 1000 epochs with a batch size of 5, and its performance is evaluated on the validation set (x_test, y_test). Early stopping is implemented to prevent overfitting, where the model training is stopped if the validation loss does not improve for a certain number of epochs.

3.3.2. Results

Below are the results obtained from CNN (Table 3).

Method	Training Accuracy	Validation Accuracy
CNN	0.810	0.871

Table 3
Results of Convolutional Neural Network

Here are reported also the loss and accuracy plots for our model during training (Figure 1 & Figure 2). The loss plot shows how the model's training loss decreased over each epoch, while the accuracy plot shows how well the model performed on the training and validation data.

The results of the CNN model show a relatively high training accuracy of 0.81, which indicates that the model has learned well from the training data. The validation

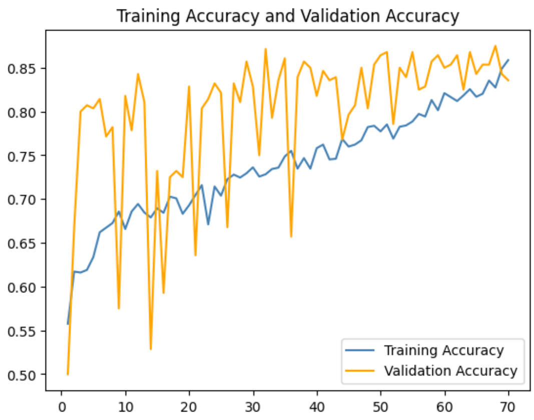

Figure 1: Model accuracy on training and validation sets during training

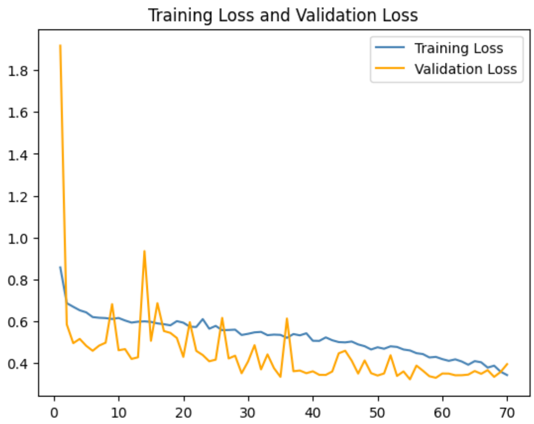

Figure 2: Model loss on training and validation sets during training

accuracy of 0.87 is even higher, suggesting that the model is also generalizing well to unseen data.

4. Conclusions

In conclusion, the results produced by CNN outperform the effectiveness of the machine learning techniques previously investigated. This implies that deep learning methods could be a useful tool for identifying autism from EEG signals. This study paves the way for additional research in this area and shows the utility of deep learning techniques for this application. Deep learning models may be further developed and optimized in order to increase the precision and reliability of autism detection, which could ultimately result in an earlier diagnosis and course of treatment for autistic people.

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