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Design and Implementation of a CNN-based Framework for Predicting Autism Spectrum Disorder

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***Abstract*— Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder, which im-pairs the communication, behavior and interaction. Early diagnosis is an important aspect of enhancing long-term results, but the standard method of diagnosing is time-consuming and requires the expert appraisal. This poses a problem especially in areas where the specialists are inaccessible. A Convolutional Neural Network (CNN) predicts ASD using the AQ-10 behavioral screening data in this research. Various performance measures such as accuracy, precision, recall and F1-score are used to evaluate the model. It is compared to the most popular ma-chine learning models like Support Vector Machines (SVM) and Random Forest. The findings suggest that CNN model is competitive and has better sensitivity in recognizing ASD-positive cases. This allows it to be a convenient early-stage screening tool. The proposed system is not designed to substitute clinical diagnosis but rather aid in the identification of individuals who might need further diagnosis.**

***Keywords*— Convolutional Neural Networks, Behavioural Screening, Deep Learning, Autism Spectrum Disorder, Ma-chine Learning.**

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a multifaceted neurodevelopmental disorder that affects the process of communication between people, their behavioral and social interactions. The condition changes in its severity amusingly making it very difficult to diagnose. In recent decades, a significant trend can be observed, toward the surge in ASD diagnosis, highlighting the significance of early diagnoses and intervention.

A diagnosis at an early age can go a long way in enhancing the quality of life of people with ASD by facilitating an early life therapeutic intervention. Nevertheless, traditional diagnostic practices are much more diagnostic oriented and based on clinical observation, systematic evaluations performed by qualified specialists. Not only are these highly time-consuming processes, but they might also be unavailable in some regions because of the lack of specialists.

As data-driven technologies are being developed, machine learning has became a promising unpaid method to assist in early screening. The models are capable of examining the behavioral data trends and any possible indicators of ASD. Although these systems cannot substitute professional diagnosis, they can serve as aids that help to detect the challenging at an early stage.

This paper aims at comparing the classic machine learning models and a deep learning framework, which constitutes a Convolutional Neural Network (CNN) and comparing their capability to predict ASD with screening data.

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II. Literature Survey

The study of ASD detection has been changing with time. Traditional machine learning techniques were mainly studied in earlier studies. As an illustration, Thabtah (2017) examined decision trees and Naive Bayes classifiers to analyze behavioral screening data and noted positive outcomes in the aspect of accuracy of the classification.

With the enhanced computational power, scientists have started to consider deep learning methods. Tariq et al. (2020) utilized convolutional neural networks on the facial images to determine the patterns that are related to ASD. Their re-sults implied that deep learning models can retrieve fine features, which are hard to identify when applied in traditional systems.

Eslami et al. (2021) suggested a hybrid approach that will be a composite of CNN and Long Short-Term Memory (LSTM) networks. The strategy enabled the system to handle both spatial and sequence data pro-cessing, causing an en-hancement in the performance of the prediction.

Newer comparative experiments, like Bandla and Dutta (2022) have demon-strated that deep learning models tend to have superior performance compared to the traditional machine learn-ing algorithms with complex datasets. These results show an ever-lasting inclination towards the application of CNN-based methods in the detection of ASD.

III. Design

A. Dataset

The data employed in the current research is also taken at the UCI Machine Learning Repository and it is based on the AQ-10 screening test. It has 7,175 examples of 14 features.

The dataset includes:

- Ten behavioural features (A1–A10 scores)
- Demographic attributes such as age, gender, and family history

The target variable is binary, indicating whether an individual is likely to have ASD.

B. Data Preprocessing

Various preprocessing tasks prior to training the models were performed. Gender and family history (categorical variables) were translated into numerical through label encoding. The step is necessary to make it compatible with ma-chine learning algorithms. The data were normalized with the feature scaling in order to avoid domina-tion of the learning process by one feature. Also stratified sampling was used to divide the data into training and testing subsets to preserve class distribution.

As the dataset had class imbalance, the weights of the classes were used dur-ing training. This aided in making sure that the models were attentive to instanc-es of minor-ty classes.

C. Algorithms used

Convolutional Neural Network

The main model applied in this work is the Convolutional Neural Net-work(CNN). The design of a one-dimensional CNN architecture was aimed to process AQ-10 behavioural and demographic features.

The model comprises of several layers that include dense layers, batch nor-malization, and dropout. These layers enable the model to learn more complicat-ed patterns as well as minimize the potential of overfitting.

The CNN was optimized with the Adam optimizer with the binary cross-entropy loss. The premature halting was used to eliminate unnecessary training when the model performance ceased to improve.

To enhance the ability to identify the cases of ASD-positive cases, the deci-sion thresh-old was slightly optimized, which makes the model more sensitive to identify the purposes to screen.

D. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is employed as a benchmark model. It is a famous supervised learning algorithm which operates by incurring the most pref-erable boundary (or hyperplane) to differentiate between the classes.

In the current study, SVM was applied with Radial Basis Function (RBF) ker-nel that enables the model to deal with non-linear data-associations.

All was scaled by standardization prior to the training since the SVM is sensi-tive to magnitude of input values. This model had also been set to give the prob-ability outputs making it to be easier to compare its performance based on measurements such as ROC-AUC.

E. Random Forest (RF)

Random Forest is an ensemble technique of learning that constructs various decision trees and integrate the results of the trees so as to offer the outputs of the tree.
The model implemented here was set with a small number of trees and a depth which was controlled. This allows avoiding the overfitting and still retaining the important patterns in data.
A strength of Random Forest is that it can process both numerical and categor-ical data without the use of the complicated transformations. It also provides information on the importance of features and can thus help in determining which inputs have the greatest contribution to the prediction.
Its results were comparable to CNN and SVM albeit at a lower level, but it has yielded consistent and understandable results.

D. Proposed CNN-based ASD Prediction Framework

The proposed system utilizes a Convolutional Neural Network (CNN)-based framework for predicting Autism Spectrum Disorder (ASD) using AQ-10 behav-ioural screening data and demographic attributes. The framework consists of five major stages: data preprocessing, feature encoding and scaling, model training, performance evaluation, and ASD prediction.
Initially, the dataset is preprocessed by handling missing values, encoding categorical features, and applying feature scaling. The processed data is then divided into training and testing sets using stratified sampling to preserve class distribution. To address class imbalance, class weights are incorporated during model training.
The CNN model employs dense layers, batch normalization, and dropout lay-ers to learn complex patterns from behavioural and demographic features while reducing overfitting. Early stopping is used to improve generalization perfor-mance. Finally, the trained model is integrated with a Streamlit-based user inter-face that allows users to enter AQ-10 responses and obtain ASD prediction re-sults in real time.
The proposed framework is designed as an early screening support tool and is not intended to replace professional clinical diagnosis.

IV. Implementation

A. Data Preprocessing

The dataset utilized in this research has both nominal and numeric features and thus it needed a bit of processing and the models were trained. Label encod-ing was used to encode categorical variables into numerical values, e.g., gender, or family history.
Following the encoding, the data was scaled using feature scaling to normalize it. This measure will make sure that none of the features will take up more ground than the other, during training and no single feature will take over the others since it is bigger. Moreover, the absent values in the data set were eliminated by deleting half-filled records. This ensures continuity and prevents mistakes when training model.

B. Data Split

To measure the performance of the models adequately, the dataset was split to training and testing sets. A split of 80:20 was chosen with 80 % of the data being used to train and the remaining 20 % to test the model.
Splitting was done using stratified sampling so as to maintain the original dis-tribution of classes. This is notably necessary since the data is a bit skewed, and keeping such a balance insures the training and testing datasets are representa-tive.

C. Model Training

The pre-processed dataset was used to train all the three models, including SVM and Random Forest, and CNN. The use of an RBF kernel to train the SVM model and a fixed number of decision trees to train the Random Forest model was in case of overfitting which was minimized by limiting the number of decision trees and the depth of the trees in the model. A more detailed setup was needed in the CNN. It was optimized by the Adam optimizer and binary cross-entropy loss on several epochs. Early termination was employed in a way that training was terminated when the performance of the model ceased to improve. There were also class weights to make sure the model did not overlook minority class samples.

D. Evaluation

All models were tested on a variety of performance measures (such as accura-cy, precision, recall and F1-score) after training. These metrics give a balanced knowledge on the model performance.

The analysis on the capability of each model to classify the positive and nega-tive cases was also carried out using confusion matrices. Besides, ROC curves were plotted to investigate the effectiveness of each model used to differentiate between classes at various thresholds.

E. Comparative Analysis

In order to have a clear understanding of the differences among models their results have been presented side by side. Rather than evaluating using one meas-ure, several evaluation measures have been used in a combination.
Based on this comparison, the CNN had a better recall by a slight margin, that is, was more effective in identifying the ASD-positive cases. It is so especially in screening applications where failure to imply a positive case can have grave con-sequences.
Despite the fact that SVM also did a good job, the CNN was able to capture complex trends in the data better.

V. Results

The overall accuracy between the three models varied marginally as they all had good performance. But the further analysis showed that certain significant dif-ferences existed.

TABLE I. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
SVM	0.9463	0.9505	0.9463	0.9471	0.9716
Random Forest	0.9045	0.9040	0.9045	0.9042	0.9648
Convolutional Neural Network	0.9456	0.9519	0.9456	0.9466	0.9812

The CNN achieved the highest ROC-AUC score of 0.9812, indicating superior capability in distinguishing ASD-positive and ASD-negative cases. Although SVM achieved a slightly higher accuracy of 94.63% compared to CNN's 94.56%, the CNN demonstrated better overall screening effectiveness through improved sensitivity and stronger ROC performance. Random Forest achieved comparatively lower performance across most evaluation metrics. These findings suggest that the CNN model is effective in capturing complex behavioural patterns and can serve as a reliable ASD screening support tool.

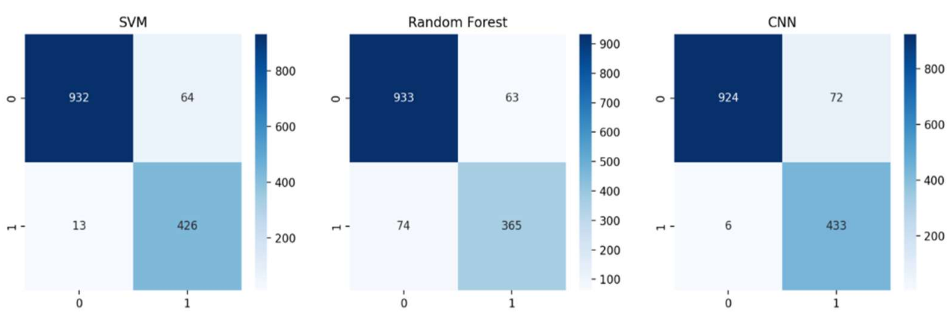

Fig. 1. Confusion matrices of SVM, Random Forest, and CNN classifiers

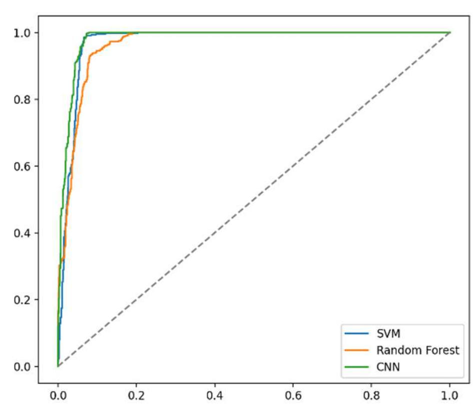

Fig. 2. ROC Curve Comparison of SVM, Random Forest, and CNN Models

The comparison of ROC curves shows the comparative performance of the mod-els at various thresholds. On the whole, the results indicate that CNN-based methods can be beneficial when it comes to working with behavioral data and describing intricate patterns.
A basic user interface has been created to express its usefulness in real-life sce-narios. The respondents are able to enter AQ1-10 responses as well as demo-graphic information including age and gender.
The system takes the inputs in question and inputs them into the trained CNN model and offers a prediction of the possibility to have ASD. The interface has been laid such that it is easy to use and intuitive even to those not technically minded.

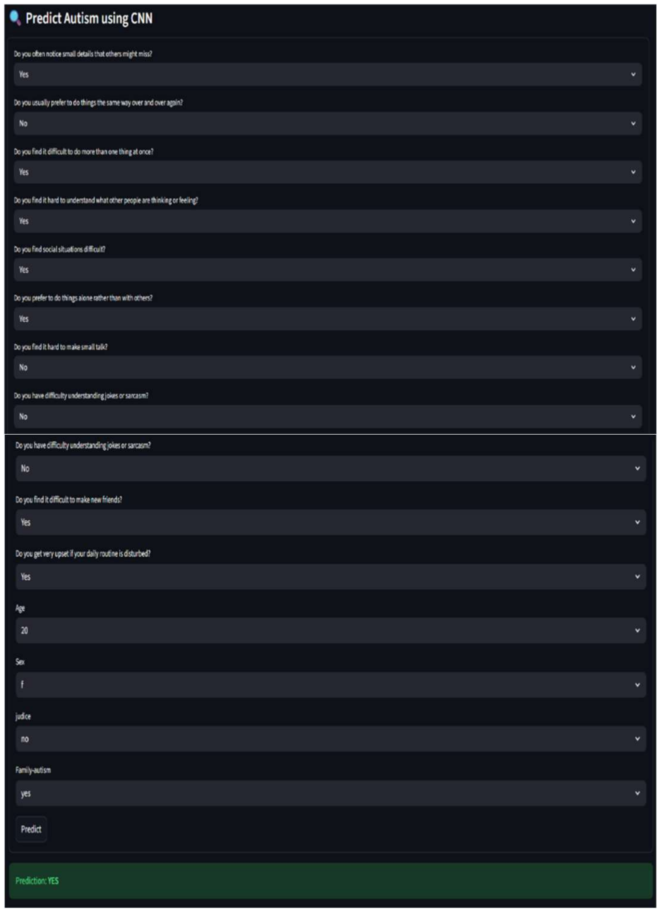

Fig. 3. Streamlit-based User Interface for ASD Prediction

Fig.3 shows the developed Streamlit-based interface that allows users to enter AQ-10 re-sponses and demographic information to obtain ASD prediction results.

VI. Conclusion and Future Work

This paper presented a CNN-based framework for predicting Autism Spectrum Disorder using AQ-10 behavioural screening data. Experimental results demon-strated that the CNN achieved competitive performance and the highest ROC-AUC score among the evaluated models. The findings indicate that CNN can effectively support early ASD screening by identifying ASD-positive cases with high reliability.
Nevertheless, the system does not aim at substituting the professional diagno-sis. Rather, it can be an aiding tool that helps in the process of isolating those, who might need additional examination.
Future research may consider including more data sources and include speech, or medical imaging, as one way of enhancing predictive accuracy. The investiga-tions of advanced architectures, as well as enhancing the interpretability of mod-els, would increase the practical applicability of the system in question.

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