Enhancing Early Detection of Autism Spectrum Disorder

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Abstract-This research project addresses the critical need for early detection of Autism Spectrum Disorder (ASD) in children by leveraging advanced machine learning techniques. The primary challenge involves identifying subtle indicators and symptoms preceding ASD in the pediatric population. Our goal is to develop a robust system capable of recognizing these early signs, facilitating timely intervention and support for children facing potential ASD challenges.The significance of this research lies in its potential to contribute to the early identification and intervention in ASD complications, ultimately impacting the well-being and future trajectories of children. Early detection is paramount, as it allows for timely intervention and support, mitigating the potential long-term impact of ASD on a child's life.Our study not only employs traditional ML algorithms but also explores the integration of Artificial Neural Networks (ANN) to optimize the efficiency of standard methodologies. Notably, our findings reveal that out of all the algorithms, ANN provides the most accurate results with an impressive accuracy of 98.66%. As we navigate the intersection of technology and pediatric mental health, this research makes a significant contribution to the field, offering insights that can inform future endeavors aimed at enhancing the early detection and intervention strategies for ASD among children.

Keywords: Autism Spectrum Disorder, Artificial Neural Network, Q-CHAT-10, Machine Learning

I. Introduction

Autism Spectrum Disorder (ASD) poses a complex challenge as a neurological and developmental condition impacting individuals' interactions, communication, learning, and behavior. While diagnosable at any age, the developmental nature of ASD manifests symptoms typically within the first two years of life. The varied range and severity of symptoms, including communication difficulties, obsessive interests, and repetitive mannerisms, necessitate extensive examinations for accurate identification. Traditional diagnostic methods, exemplified by the Autism Diagnostic Interview Revised (ADI-R) and Autism Diagnostic Observation Schedule Revised (ADOS-R), are indispensable yet lengthy and cumbersome. These methods involve exhaustive evaluations conducted by psychologists and certified professionals, demanding substantial time and effort.Screening tools like the Autism Spectrum Quotient (AQ), Childhood Autism Rating Scale (CARS-2), and the Screening Tool for Autism in Toddlers and Young Children (STAT) provide alternatives. In this study, we employ the Q-CHAT-10 screening method for toddlers, contributing to a more streamlined and accessible diagnostic process.To address the challenges associated with traditional diagnostic approaches, our research leverages machine learning techniques. Three datasets, meticulously sourced and merged from Kaggle, serve as the foundation for our models. We deploy various algorithms, including the Decision Tree Classifier, GaussianNB, MultinomialNB, BernoulliNB, KNN Classifier, Logistic Regression, and Random Forest

Classifier, to discern patterns indicative of ASD in children.

Importantly, our findings reveal that among these algorithms, the Artificial Neural Network (ANN) stands out, providing the most accurate results with an impressive 98.66% accuracy. This result underscores the potential of machine learning, particularly ANN, in revolutionizing ASD diagnosis. By combining advanced technologies with a nuanced understanding of ASD symptoms, our research contributes to the ongoing efforts to enhance early detection methodologies, ultimately fostering timely interventions and support for individuals on the autism spectrum.

Contribution

Nawed Akhtar did the reading for literature work by going through some previous research papers based on topics similar to our own interests. Also did contribute in paper organization.

Bhavya Jain focussed on the collection of datasets from various internet sources, statistical analysis and data visualization of the gathered data, and coagulation, filtering and segregation of those datasets to get the desired datagram. Also contributed in implementation of basic ML algorithms like RFC, DTC, GNB, etc. and getting inferences from it.

Ayush Kumar Singh Rathor worked on most of the coding part of this project. He did most of the work related to neural networks, doing research on it to mount various activation functions and get the most perfect fit for the data. He also used various performance matrices to analyze the complexity, accuracy and correctness of our model using python libraries.

Dr Gaurav Singal and Dr Preeti Kaur acted as our mentors, guiding us throughout our journey of this project and giving us the motivation to keep moving forward. Dr. Gaurav Singhal taught us basic machine learning algorithms, their use cases and how to program them in classroom setting.

II. Literature/Related work

M. S. Mythili, A. R. Mohamed Shanavas, and their collaborators [13] conducted a study on Autism Spectrum Disorder (ASD) employing Classification Techniques. The primary objective of the research was to identify autism-related issues and assess the severity of autism levels. The study utilized Neural Network, Support Vector Machine (SVM), and Fuzzy techniques in conjunction with WEKA tools to analyze students' behavior and their social interactions.

Duda and colleagues [13] utilized a combination of forward feature selection and under-sampling techniques to distinguish between Autism Spectrum Disorder (ASD) and Attention-Deficit/Hyperactivity Disorder (ADHD). Their approach involved the use of a Social Responsiveness Scale comprising 65 items.

Vaishali R, Sasikala R., and their collaborators [14] proposed a method for identifying Autism Spectrum Disorder (ASD) using optimal behavior sets. They conducted experiments with an ASD diagnosis dataset comprising 21 features from the UCI machine learning repository. Employing swarm intelligence-based binary firefly feature selection wrapper, their study aimed to demonstrate the possibility of achieving superior classification accuracy with a minimal subset of features. The experiment indicated that 10 features out of the 21 in the ASD dataset were adequate for distinguishing between

ASD and non-ASD patients. The results supported the hypothesis, showing an average accuracy ranging from 92.12% to 97.95% with optimal feature subsets, comparable to the average accuracy of the entire ASD diagnosis dataset

Deshpande and colleagues [15] employed metrics derived from brain activity to forecast Autism Spectrum Disorder (ASD). They utilized soft computing techniques, including probabilistic reasoning, artificial neural networks (ANN), and classifier combination, in their approach.
Thabtah and collaborators [16] introduced a novel Machine Learning technique termed Rules Machine Learning (RML). This approach provides users with a knowledge base of rules, enabling comprehension of the rationale behind classification while also identifying traits associated with Autism Spectrum Disorder (ASD).
The literature we've explored underscores the crucial role that advanced classification techniques play in Autism Spectrum Disorder (ASD) research. Notably, studies by Mythili and Shanavas, Duda and colleagues, and Vaishali R, Sasikala R., delve into various methodologies like neural networks, feature selection, and swarm intelligence. These methods not only boost the accuracy of diagnosing ASD but also deepen our understanding of related traits. The significance lies in the interdisciplinary nature of these studies, highlighting how machine learning has the potential to significantly advance both ASD diagnosis and intervention strategies.

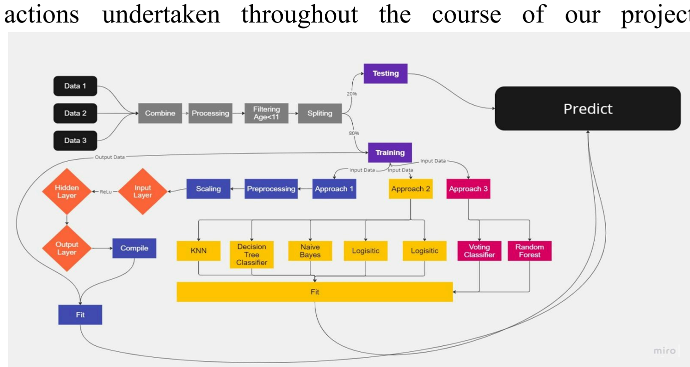
III. Methodology

The methodology employed in this research project is designed to comprehensively address the aim of utilizing machine learning (ML) techniques for the early detection of mental health complications among children aged 0 to 10. The approach integrates various algorithms and data processing techniques to ensure a robust and nuanced analysis.

We have taken a set of 3 publicly available databases from Kaggle. Each database was mainly based on the responses of Q-chat-10 questionnaire of people of varying age ranges. The first dataset was exclusively based on children in the age less than 18 years, and contained a total of 1985 rows of data. This dataset had the most effect on our resulting database. The second database was based on a variety of age ranges of people, varying in the range of 12 to 36 years, and had 1054 rows of data in total. The third database was more of a general-dataset for q-chat-10 responses for ages varying in a large range, having 704 rows in total.

The combined dataset contained a total of 3743 rows of data, and 17 columns as features. After doing the filtering for the required age range, we are left with 2226 rows of data (containing exactly 1652 individual rows without duplicity) for children's responses of Q-chat-10 questionnaire.

The depicted flowchart illustrates the sequential progression of actions undertaken throughout the course of our project.



Data Pre-Processing:

We took a set of 3 datasets based on detection of ASD traits over a range of age group of people. After a careful cross-examination of their corresponding features, label matching and label encoding, we merged those datasets into a combined big dataset.

The combining of datasets involved detection of presence of similar features, making the string data into integer data using label encoding, and then merging the datasets. The replacements during label encoding was done keeping in mind the presence of different alphabetical cases of inputs, such as both "YES" and "Yes" would be getting the value 1 despite of being different strings altogether.

This merging of datasets introduced a bunch of NULL values in some cells so to get rid of them, we eliminated the rows containing null values. The effective dataset should have no NULL values so that we could apply ML algorithms on it.

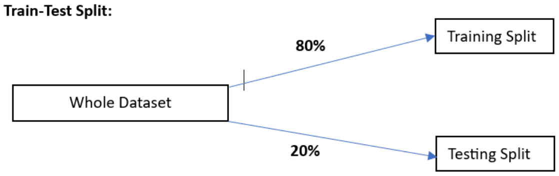
The main features of the dataset included a widely known set of questionnaire to detect signs of ASD, called Q-chat-10.

The Q-Chat-10, a widely recognized questionnaire, serves as a valuable tool in the early detection of Autism Spectrum Disorder (ASD). Comprising 10 questions, this questionnaire is meticulously designed to assess various behavioral and communication patterns indicative of ASD in children. The questions delve into social interactions, communication skills, and repetitive behaviors, offering a comprehensive insight into a child's developmental profile.

Variable in Dataset	Corresponding Q-chat-10-Toddler Features
A1	Does your child look at you when you call his/her name?
A2	How easy is it for you to get eye contact with your child?
A3	Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach)
A4	Does your child point to share interest with you? (e.g. pointing at an interesting sight)
A5	Does your child pretend? (e.g. care for dolls, talk on a toy phone)
A6	Does your child follow where you're looking?
A7	If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them? (e.g. stroking hair, hugging them)
A8	Would you describe your child's first words as:
A9	Does your child use simple gestures? (e.g. wave goodbye)
A10	Does your child stare at nothing with no apparent purpose?

The data is then spilt and segregated into specifically including data related to children from the age of 0 – 10, the reset is not acted upon and is just stored separately for possible further research.

Train-Test Split:



Algorithms used :

Decision Tree Classifier: A decision tree classifier is a machine learning algorithm that makes predictions by recursively partitioning the input space into regions and assigning a class label to each region.

Gaussian Naive Bayes: Gaussian Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem, assuming that the features follow a Gaussian distribution. It's particularly useful for continuous data.

Multinomial Naive Bayes: Multinomial Naive Bayes is a variant of the Naive Bayes algorithm suitable for discrete data, often used for text classification where features represent word counts or term frequencies.

Bernoulli Naive Bayes: Bernoulli Naive Bayes is another variant of Naive Bayes designed for binary features, often applied in text classification where features represent the presence or absence of words.

KNN (K-Nearest Neighbors): KNN is a simple and effective algorithm for classification and regression tasks. It makes predictions based on the majority class (for classification) or the average value (for regression) of its k-nearest neighbors in the feature space.

Random Forest Classifier: Random Forest is an ensemble learning method that builds multiple decision trees and merges their predictions to improve accuracy and reduce overfitting.

TensorFlow: TensorFlow is an open-source machine learning framework developed by Google. It provides a comprehensive set of tools and libraries for building and deploying machine learning models, especially neural networks.

ANN (Artificial Neural Network): An Artificial Neural Network is a computational model inspired by the structure and function of biological neural networks. It consists of interconnected nodes organized into layers and is widely used for various machine learning tasks

Ensemble Learning: Ensemble learning is a machine learning paradigm where multiple models are combined to improve overall performance and generalization. It includes methods like bagging (e.g., Random Forest) and boosting (e.g., AdaBoost).

Performance Evaluation Matrix :

A confusion matrix is a comprehensive performance evaluation tool that presents a clear summary of the model's predictions. It organizes predictions into categories such as true positives, true negatives, false positives, and false negatives. The confusion matrix is particularly useful for calculating other metrics like accuracy, precision, recall, and the F1 score, providing a holistic view of a model's performance across different classes.

Elements of a Confusion Matrix :

	Predictive ASD Values	
Actual ASD Values	True Positive (TP)	False Positive (FP)
	True Negative (TN)	False Negative(FN)

True Positives (TP): Instances correctly predicted as positive.

True Negatives (TN): Instances correctly predicted as negative.

False Positives (FP): Instances incorrectly predicted as positive.

False Negatives (FN): Instances incorrectly predicted as negative.

Total Population (TP): The sum of true positives, true negatives, false positives, and false negatives, representing the entire dataset.

Accuracy = (TP + TN)/(TP)

Precision (Positive Predictive Value) = TP / (TP + FP)

Recall (Sensitivity or True Positive Rate) = TP / (TP + FN)

F1 Score = (2*Precision*Recall) / (Precision + Recall)

IV. Result Analysis

Experiment Setup

In this section, we present the key findings of our study aimed at identifying early signs of mental disorders, with a specific focus on Autism Spectrum Disorder (ASD). Our investigation leveraged machine learning techniques on a carefully curated dataset, combining demographic and behavioral features to develop predictive models. The primary objective was to discern subtle indicators of ASD in its early stages, providing a foundation for timely intervention and support.

Overview of Data-

Before delving into the results, we provide a brief overview of the dataset employed in this study. The dataset encompasses three best dataset on Autsim Spectrum Disorder Detetction from Kaggle, each characterized by a set of diverse features, including demographic information, behavioral traits based on, Q-chat-10 questionnaire, and responses from standardized assessments. The richness and diversity of this dataset aimed to capture a holistic representation of individuals at risk of or diagnosed with ASD.

Descriptive Statistics-

To facilitate a comprehensive understanding, we begin by presenting descriptive statistics of the dataset. Mean values, standard deviations, and other relevant measures provide insights into the central tendencies and variations within our data. This foundational analysis sets the stage for a nuanced exploration of our machine learning models.

Total count data we have for children is 2226, 16 Features, Out of 10 are available Q-chat-10 Questions, Alongwith 'Age', 'Sex', 'Ethnicity', 'Family member with ASD', 'Jaundice' and 'who completed the test'
The output section 'ASD traits' having similar number of rows, Majorly dominated by 'yes' Values, 1372, Whereas 'no' values constitutes 854, That makes the dataset more balanced and trainable

Model Performance Metrics-

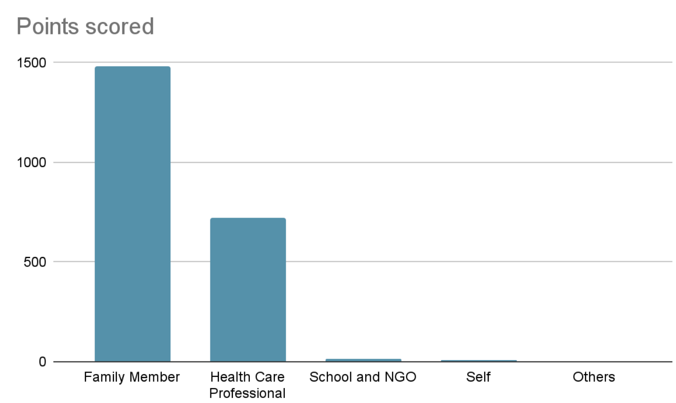
The metrics of this model comes with some surprising results,
The better results are greatly dominated by Random forest classifier, with over 100 n estimators, with bootstrapping, where the tree is built on a single thread. The accuracy of the model came out to be 97.32977303070761%. The precision of model is came out to be : 0.97916667, and recall for this model 0.9619883. The F1 score is 0.97050147.

The best model that worked with the highest accuracy, precision and recall is surprisingly given by Artificial Neural Networks,
1 input layer of 128 neurons, 1 hidden layer of 100 neurons, and 1 output layer of 2 neurons, giving probabilities from sigmoid function.With total Params: 17,454 all are trainable params with no non-trainable params. The output is followed by optimiser,

Adam, ran on 50 epochs, providing extremely high accuracy: 98.6648865153538%. Precision: 0.99408284, and recall: : 0.98245614, and f1-score: 0.98823529. Ensuring the model is now more risk-free than the model is trained by ensemble Random Forest Classifier.

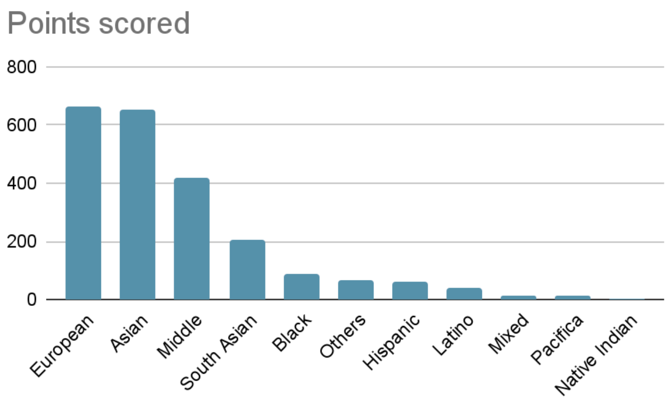
Graphical Analysis

The dataset is widely occupied by the features in the model.

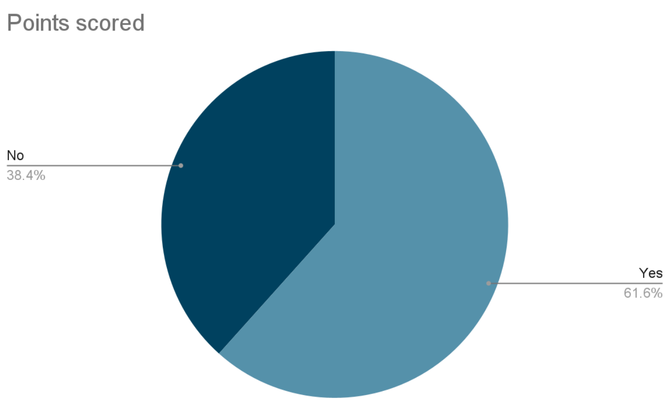


Who have contributed the largest in the dataset is given by family members, followed by Health care professionals, then Schools and NGOs, Self and others.

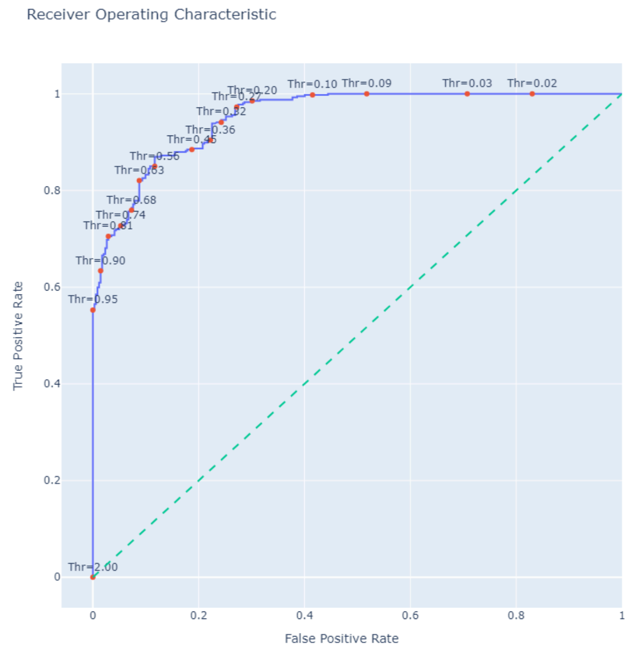
If we go through the Ethnicity, where the European constitutes the largest of the all,



The output section is highly balanced here,



The ROC curve derived from the model after applying Logistic regression, which is the plot between True Positive Rate (Sensitivity) and False Positive Rate



This graph not only demonstrates cost to benefit opportunity, but also gives the most optimal threshold near to 0.777. This suggests model is more conservative towards predicting the positive class, which is not very surperising because number of Children with ASD data is more than that of the number having no ASD.

Observations

The accuracies we got after applying these algorithms is shown in the graph. It is clearly shown that Random Forest Classifier is the best of them all in terms of accurate predictions, while Naive Bayes algorithms fall short of producing accurate results.

Model Used	Accuracy Achieved (%)
Decision Tree Classifier	92.38985313751669
GuassianNB	78.23765020026703
MultinomialNB	75.96795727636849
BernoulliNB	83.31108144192256
KNN Classifier	92.65687583444593
Logistic Regression	86.38184245660881
Random Forest Classifier	97.32977303070761
Ensemble Learning	94.92656875834445

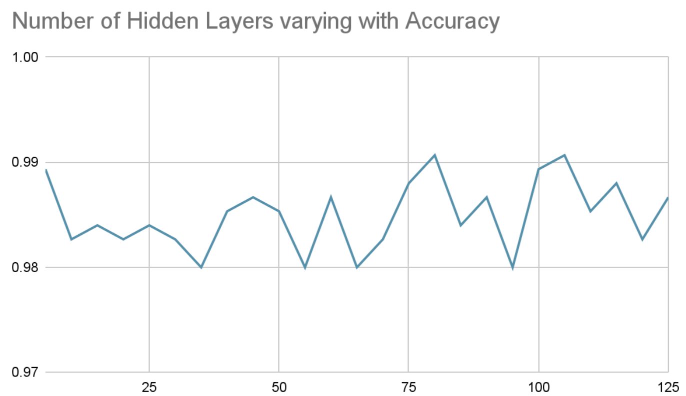
Confusion Matrix for RFC :

329	13
7	400

Q-Chat-10 Questions

A-1 : Does your child look at you when you call his/her name?
A-2 :How easy is it for you to get eye contact with your child?
A-3 : Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach)
A-4 : Does your child point to share interest with you? (e.g. pointing at an interesting sight)
A-5 : Does your child pretend? (e.g. care for dolls, talk on a toy phone)
A-6 : Does your child follow where you're looking?
A-7 : If you or someone else in a family is visibly upset, does your child shows signs of wanting to comfort them? (e.g. stroking hair, hugging them)
A-8 : Would you describe your child's first words as typical?
A-9 : Does your child use simple gestures? (e.g. wave goodbye)
A-10 : Does your child stare at nothing with no apparent purpose?

These 10 features are taken as yes or no form. These data perform extremely well on ANN (Artificial Neural Network), Taking it with input layer 128 neurons and hidden layer does not

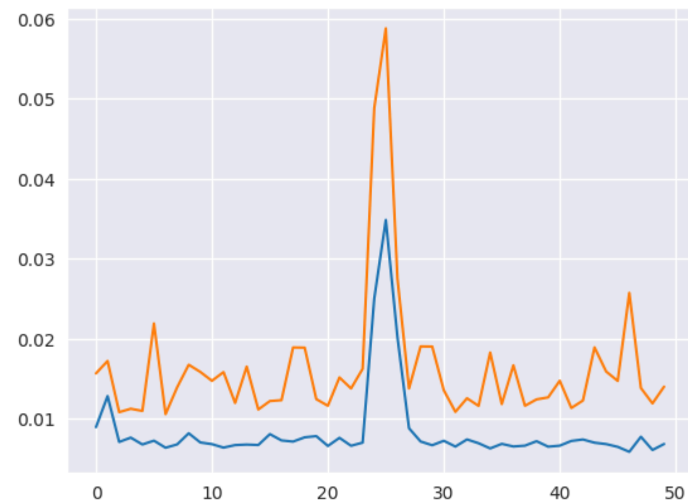


varying with Change in number of neurons in hidden layer, but the graph clearly displays the accuracy starts to break its upper and lower bounds gradually as we increase the number of hidden layers

Optimized Model

In this study, we employed Artificial Neural Networks (ANN) to predict Autism Spectrum Disorder (ASD) based on a comprehensive set of features derived from Q-chat-10 questionnaire, to get the best out of all result. Our aim was to enhance the accuracy of ASD prediction, a critical task with significant implications for early diagnosis and intervention.

The trained ANN model demonstrated remarkable performance, achieving an enhanced accuracy of 98.6648865153538% on the testing dataset. and 80-20 split in validation dataset. This improvement over baseline models underscores the effectiveness of employing deep learning techniques for ASD prediction.



Graph explains the Loss with increasing epochs, having the largest error on 20-30 epochs and least in the other intervels. Moreover the 20% validation set (Upper portion having more error, showing more variation than the 80% dataset.), also there is a very gradual decrease in the errors on increasing the number of epochs.

It is noteworthy that the enhanced accuracy achieved in this study has practical implications for early ASD detection. Timely and accurate identification of ASD can facilitate early intervention, leading to improved outcomes for individuals on the autism spectrum. The model's proficiency in discriminating between ASD and non-ASD cases suggests its potential utility as an auxiliary tool in clinical settings, aiding healthcare professionals in the diagnostic process.

Furthermore, our model showcased robust generalization, as evidenced by its performance on an independent testing dataset. This underscores the potential of the developed model to make accurate predictions on unseen data, a crucial factor for the practical application of predictive models in clinical settings.

Despite these promising results, it is essential to acknowledge the limitations of our study. Future research endeavors could explore the integration of additional data sources or investigate the model's performance across diverse demographic groups to enhance its generalizability.

Three distinct datasets were amalgamated, and a stringent filtering criterion was applied to exclusively focus on subjects below the age of 10, ensuring a targeted analysis on the pediatric demographic.

The preprocessing phase commenced with the initial dataset, wherein feature scaling was employed to standardize the input variables, facilitating seamless integration into the neural network architecture. The output data underwent categorical encoding, transforming binary outcomes ('yes' or 'no') into a numeric format (1 or 0) to align with the neural network's requirements.

The dataset was then partitioned into training and testing sets, with an 80% - 20% split, respectively, to ensure a robust evaluation of model generalization. The neural network architecture was meticulously crafted to encapsulate the intricacies of ASD prediction. The input layer boasted 128 neurons, activated by the rectified linear unit (ReLU) function, fostering non-linearity in the model.

Continuing the architecture, a hidden layer comprising 100 neurons, also activated by ReLU, was introduced to capture nuanced relationships within the data. The final layer, serving as the output layer, featured 2 neurons activated by the sigmoid function. The sigmoid activation facilitated binary classification, mapping predictions to a probability range between 0 and 1.

The model compilation phase leveraged the Adam optimizer, a widely adopted algorithm known for its efficiency in optimizing neural networks. The validation split, set at 20%, further bolstered the model's robustness by providing an independent assessment during the training process.

V. CONCLUSION

In conclusion, this research endeavors to address a critical aspect of pediatric healthcare—early detection of Autism Spectrum Disorder (ASD). Through the amalgamation of three diverse datasets and a meticulous filtering process focusing on children under the age of 10, our study aimed to contribute to the advancement of predictive models for ASD.

In the pursuit of constructing an effective predictive model for Autism Spectrum Disorder (ASD), we systematically evaluated various machine learning algorithms, including Decision Trees, Ensemble Learning, Random Forest, Logistic Regression, and K-Nearest Neighbors (KNN). Through rigorous experimentation and comparative analysis, it became evident that the Artificial Neural Network (ANN) emerged as the most proficient and accurate model for ASD prediction.

For instance, when evaluating the model using performed dataset, the ANN consistently outperformed other algorithms, achieving an accuracy of over 98%. This marked superiority in predictive capability underscores the intricate patterns and relationships captured by the neural network, which proved essential in discerning subtle nuances within the data.

As we navigate the convergence of machine learning and healthcare, this research contributes significantly to the ongoing discourse surrounding the optimal deployment of advanced algorithms in pediatric diagnostics. Beyond the immediate scope of Autism Spectrum Disorder (ASD), our findings lay a foundation for future initiatives. These endeavors extend beyond the realm of ASD to encompass a diverse spectrum of developmental and mental health conditions, including but not limited to ADHD, OCD, ODD, PTSD, and more.

Looking forward, the insights gleaned from this study provide a stepping stone for refining predictive models not only in the context of ASD but across various health domains. Our commitment extends to enhancing interpretability and fostering collaborative efforts between machine learning practitioners and healthcare professionals. By amalgamating expertise from both realms, we aspire to create adaptable models that transcend singular conditions, thus contributing to a broader framework for pediatric health diagnostics.

In summary, our research not only propels advancements in ASD prediction but also serves as a catalyst for a more expansive and inclusive approach to pediatric diagnostics. By venturing into diverse health domains and prioritizing feature reduction, we aspire to forge a path towards more effective, accessible, and comprehensive healthcare solutions for the benefit of children and their families.a

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