Detection of Autism Spectrum Disorder using Deep Neural Network

MSc Research Project
MSc Data Analytics

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MSc Project Submission Sheet

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DETECTION OF AUTISM SPECTRUM DISORDER IN TODDLERS USING DEEP NEURAL NETWORKS

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ABSTRACT

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by neurological variations. Individuals diagnosed with Autism Spectrum Disorder (ASD) may exhibit distinctive patterns of behavior, communication, social interaction, and cognitive processes that differ from the typical functioning observed in the majority of the population. Autism Spectrum Disorder (ASD) frequently appears at age three and can last a lifetime, however symptoms may improve over time. Some children show indicators of Autism Spectrum Disorder (ASD) in their first year. A child may not show symptoms until 24 months or older. Some children with Autism Spectrum Disorder (ASD) learn new skills and reach developmental milestones by 18–24 months. The condition's wide range of behavioral and verbal symptoms makes it hard to identify, especially in toddlers. Due to time-consuming clinical tests and high financial expenses, Autism Spectrum Disorder (ASD) diagnosing processes stress healthcare personnel. The advent of machine learning and deep learning in the medical domain presents a potentially advantageous resolution. This study introduces a novel approach by employing a Deep Learning architecture to significantly enhance the early identification of Autism Spectrum Disorder (ASD) in toddlers. The methodology relies on the utilization of an Artificial Neural Network (ANN), which is a method of Deep Learning. Through the use of this method, the study seeks to augment diagnostic accuracy and optimize the diagnostic procedure. This study represents a significant progress in the early diagnosis of Autism Spectrum Disorder (ASD), utilizing the ability of Artificial Intelligence (AI) to transform diagnostic methodologies in order to improve the healthcare outcomes for toddlers. The trained model is tuned using hyper-parameters which gave the best performance of the model. The accuracy of the suggested artificial neural network (ANN) model after tuning was found to be 98%. This suggests that our approach represents effectiveness for the diagnosis of Autism Spectrum Disorder (ASD) in toddlers. If implemented, this method might enable parents to immediately provide suitable therapy that reduce the symptoms of ASD.

Keywords— ASD, Deep Learning, diagnosis, Accuracy, Artificial Neural network, therapy

1. INTRODUCTION

Autism spectrum disorder (ASD) is a complex and heterogeneous illness that affects the neurological system. Among the developmental challenges are those with communication, social skills, emotional deficiencies, and sensory disorders. Autism is a disorder that is hard for parents or average people to identify, therefore individuals should speak with a physician or pediatrician (Nabila Zaman, 2021) . Autism Spectrum Disorder (ASD) often develops before to the age of three and can persist throughout an individual's lifespan. While many individuals express signs of ASD during their first year of life, others may not display any indications until reaching the age of two years. Another reason for the diagnosis of Autism Spectrum Disorder (ASD) in adults or at a later age is the lack of awareness among parents regarding ASD. As a result, when these individuals reach adulthood, they may encounter challenges in establishing and sustaining friendships, communicating with both peers and adults, and understanding appropriate behaviors in educational and workplace environments. In the end individuals with ASD may experience anxiety, depression, or attention-deficit/hyperactivity disorder as a result (Venkata Satya Sai Karri, 2023). Traditional diagnostic techniques include Autism Diagnostic Interview Revised (ADI-R) and Autism Diagnostic Observation Schedule Revised (ADOS-R). Yet, these procedures are complex, expensive and time-consuming (Purkayastha, 2021). In the United States, it has been observed that parents have paid up to $1.2 million for the purpose of autism identification. (Mengwen Liu, 2013), this highlights the concept for an alternate method to early-stage diagnosis of Autism Spectrum Disorder (ASD), which not only improve the health of individuals but also reduces expenditures on unneeded medical procedures and saves time.

The objective of this study is to detect Autism Spectrum Disorder in toddlers using Deep Neural Network in range between 12 to 36 months. The dataset for model implementation is created using the toddlers ASD datasets created by Dr. Fayez Thabtah. In recent years, a considerable body of research has been conducted to examine the diagnosis of ASD using machine learning and deep learning techniques. The author (Minhazul Hasan, 2021) used both adult and toddler datasets for the detection of an ASD using Machine learning algorithm, on toddler dataset attained 97% is the highest accuracy and on adult attained a 100% accuracy they have evaluated their model’s performance by accuracy and efficiency but while using machine learning algorithms the model tend to show overfitting or under-fitting issues and loss of data. To increase the accuracy of the model, reduce the loss function and to avoid the overfitting and under-fitting issues we have used the Artificial Neural Network (ANN) a deep learning method. The advancements in Deep learning models have enhanced the potential for accurate predictions and classifications in the early identification of Autism Spectrum Disorder (ASD) and other disorders. The model is also tuned using Hyper-parameter for better results which involves in finding the best combination of parameters such as learning rate, batch size, activation function, optimizer, batch normalization and number epochs.

In this research the remaining sections are organized as follow: Section 2 – is the literature review, a report of similar research works. Section 3- Research Methodology- discussion about research procedure. Section 4- Design Specification – Specifies the proposed framework. Section 5- Implementation – Discussion of final stage of implementation of proposed solution. Section 6- Evaluation – Presenting the results and main findings and discussions to support my research question. Finally Section 7- presents the Conclusion and Future Works of my research work.

2. LITERATURE REVIEW

2.1 Machine Learning

The study conducted by (Nabila Zaman, 2021) introduced a system that has the capability to diagnose autism without the need for professional intervention. The system aims to provide reliable and valuable results that may be beneficial for parents. The author employed six different approaches, including support vector classifiers, K-Nearest Neighbors, logistic regression, Naïve Bayes, decision tree, and random forest, to analyze the child ASD dataset. Among these methods, Naïve Bayes exhibited superior accuracy and efficiency. Consequently, by utilizing this technology, parents are able to promptly ascertain their child's whereabouts and provide essential medicine in a timely manner, so optimizing parental efficiency.

In their study (Minhazul Hasan, 2021), (Venkata Satya Sai Karri, 2023) put out the proposition that the identification of Autism Spectrum Disorder (ASD) may be achieved by the examination of biological imaging and social media data. In this particular case, the identification of Autism Spectrum Disorder (ASD) is based on facial characteristics such as lip, nose, and eye distance in a certain image and arrangement. This work focuses on the utilization of DenseNet Machine Learning models for the purpose of face picture classification. The assessment criteria used in this study include statistical factors such as sensitivity, specificity, and accuracy. In order to improve the accuracy of the results, data augmentation is employed, which involves increasing the size of the test dataset. This highlights the significance of having a flawless dataset in the model development process. The study concludes that the models have the potential for further improvement through the integration of DenseNet with supplementary deep learning methodologies.

In their study, (Minhazul Hasan, 2021) put out a method for detecting Autism Spectrum Disorder (ASD) in both adult individuals and toddlers. Based on the conducted study, seven machine learning algorithms were employed on two datasets. The XGBoost, Gradient Boosting algorithms, and random forest classifier shown superior performance in terms of outcomes. In order to ascertain the noteworthy characteristics inside the dataset, researchers employ certain statistical methodologies such as the Mann-Whitney U test and the Chi-square test. The min-max normalization approach was employed to transform the coefficient values into the range of 0 to 1. Furthermore, the matrices pertaining to accuracy, recall, and f1 score utilized for model assessment yielded a commendable result in the research study.

The rising prevalence of Autism Spectrum Disorder (ASD) and the requirement for early intervention programs are discussed by the author (Mengwen Liu, 2013). It investigates machine learning methods for exploiting Early Intervention (EI) information to diagnose ASD early. To discover significant traits, the study creates an ASD ontology. For maximum performance, Support Vector Machine (SVM) is used using ontology-based unigrams. The potential of automated methods to locate probable ASD cases in non-standard EI records is shown by encouraging results. The variety of languages used in EI data presents difficulties, and using unigrams to accurately describe ASD traits is difficult. However, non-standardized text data from EI records can help in addressing important ASD-related public health concerns. To increase classifier performance in early ASD detection and intervention, more advancements and research into bigrams are recommended.

The research undertaken by (C.Karpagam, 2022) in 2022 utilized machine learning techniques, namely logistic regression, to examine a dataset about autism in individuals spanning several age cohorts, including toddlers, children, adolescents, and adults. The author utilized chi-square and Information gain as techniques for selecting features. The logistic regression model demonstrated great performance as a result of the decreased data volume in each dataset. When comparing the study done by [3] to other machine learning algorithms, it was seen that the latter exhibited higher performance and achieved greater levels of accuracy.

In the study conducted by (Surati Ningsih, 2021), a mobile application designed exclusively for children with autism was developed. This tool has the potential to aid parents in monitoring the health of their children starting from the initial manifestation of symptoms related to Autism Spectrum Disorder (ASD), therefore enabling them to take necessary actions. The method they have used is waterfall method and also called linear algorithm. It is recommended that the application be utilized for infants who have reached a minimum age of 18 months. Infants who are 12 months of age are also identifiable within the scope of our research.

The report (Shirajul Islam, 2020) examines ASD and the relevance of early diagnosis. It shows that one in 59 children has ASD, and early identification can improve therapy. The research also covers diagnosing ASD in children with machine learning methods. K-NN, Naive Bayes, SVM, and Random Forest algorithms are used for experimentation. The research finishes with the objective of building an online tool that uses machine learning to accurately diagnose autism early on. The paper's proposed web tool has not been constructed or evaluated, therefore its effectiveness and usability are uncertain.

The objective of this study (Parikh MN, 2019) was to evaluate the influence of personal characteristic data (PCD) on enhancing diagnostic models for Autism Spectrum Disorder (ASD). In this study, a carefully curated dataset sourced from ABIDE was utilized, comprising a total of 851 participants encompassing both persons diagnosed with Autism Spectrum Disorder (ASD) and control subjects. The primary objective of the study was to evaluate the performance of nine distinct supervised machine learning models. The participants were categorized by the models according to six personal factors, including age, sex, handedness, and several measurements of IQ. The neural network model exhibited superior performance, with a mean AUC of 0.646, while the k-nearest neighbour technique closely trailed behind with a mean AUC of 0.641. The results of the feature selection analysis indicated that full-scale IQ, verbal IQ, and performance IQ had the highest predictive value among the assessed features. The neural network demonstrated equivalent findings in terms of AUC by just considering these three characteristics. The study proposes that the integration of PCD (Personality and Clinical Data) has the potential to improve ASD (Autism Spectrum Disorder) diagnostic models and perhaps facilitate automated clinical diagnosis when supplemented with additional discriminative characteristics such as neuroimaging.

The paper (Muhammad Shoaib Farooq, 2021) performs different ways that Autism Spectrum Disorder (ASD) can be found in both children and adults. The review looks at studies that used medical images and wearable devices with sensors as well as analysis of behavior, facial expressions, structure, emotions, and mental disorders. The paper also talks about the problems that come up when trying to get patient information because of organizational rules and area laws about data protection. It also talks about problems with data security, privacy, and availability. The paper suggests using Federated Learning (FL) as an advanced machine learning method to deal with these problems. FL does this by keeping data with the organization that made it and training a small-sized local data model from onsite data. This model is then sent over the network to a central server, where all the local models are combined to train a Meta classifier to figure out which ML model is best at detecting autism.

The author (Mohanty, 2021) uses many methods to diagnose Autism Spectrum Disorder (ASD). Feature analysis, machine learning classifiers, principal component analysis, deep neural networks, and variable analysis are a few of the approaches covered in the study. The performance of several classifiers, including Naive Bayes, Logistic Regression, J48 Decision Tree, Surface Vector Machine, K Nearest Neighbors, and Multilayer Perceptron, is also compared by the authors. The research also addresses the usage of ASDTest, a mobile-based ASD screening tool, and how well it works to detect ASD. The authors also discuss the research's shortcomings, including the omission of toddler occurrences because of their uneven character and infrequent availability.

2.2 Deep Neural Networks

In order to enhance the accuracy of categorization, scholarly investigation is required. The researcher (Muhammad Faiz Misman, 2021) conducted a study where they used a deep neural network (DNN) architecture to two datasets including adult autism spectrum disorder (ASD) screening data. They then compared the performance of their DNN approach to a previously existing machine learning method, namely the Support Vector Machine (SVM) algorithm. This research aims to mitigate the risk of overfitting in deep neural networks (DNNs) by implementing two strategies: restricting the number of epochs and including the dropout hyperparameter. The results demonstrate that both approaches significantly enhance the performance of the DNN classifier. In terms of accuracy, the DNN classifier has demonstrated superior performance compared to the SVM. Finally, the author suggests that in order to get enhanced performance of deep neural networks (DNN), it is imperative to utilize a larger dataset.

According to a study conducted by (Purkayastha, 2021), a set of five machine learning algorithms were suggested for the purpose of identifying Autism Spectrum Disorder (ASD) in toddlers. The performance of these models was assessed using evaluation metrics such as F1 score and precision-recall. In order to enhance the velocity and effectiveness of training, feature engineering is conducted, resulting in a reduction in data dimensions. The top-performing models in this study were Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM). In addition, the author intends to employ deep learning techniques that integrate convolutional neural networks (CNNs) with a larger dataset to improve the ability to generalize. In the study conducted by (Muhammad Faiz Misman, 2021), the authors discuss the need of utilizing larger datasets while adopting Deep Learning algorithms in order to enhance performance. In our research, artificial neural networks (ANN) are employed as a methodology for constructing models.

The author (Brosh, 2019) examines the application of automated acoustic-prosodic analysis as a potential method for early identification of Autism Spectrum Disorder (ASD) in pre-verbal toddlers. Prior research has primarily examined the speech patterns of older children who possess advanced verbal abilities. However, the present study aims to explore the vocalizations exhibited by toddlers at the age of 18 months. Data was obtained from a sample comprising high-risk siblings of children diagnosed with Autism Spectrum Disorder (ASD) and a control group consisting of typically developing individuals. The study employed two classifiers, namely support vector machine (SVM) and probabilistic neural network (PNN), for the purpose of classifying participants using acoustic-prosodic features. The performance of the PNN classifier surpassed that of the SVM classifier, exhibiting accuracy, sensitivity, and specificity levels exceeding 95%. This improvement reached up to 50%. The study posits that early vocalizations may exhibit markers indicative of Autism Spectrum Disorder (ASD), thereby facilitating clinicians in the timely identification of the condition. Additional research is required to validate these findings and encompass toddlers diagnosed with alternative language development disorders. Future research endeavors to expand the scope of analysis to encompass audio data obtained during the 9- and 12-month assessments.

The study (Suman Raj, 2019) examines machine learning methods for analyzing and detecting Autism Spectrum Disorder (ASD) across a range of age groups. It compares different algorithms using non-clinical ASD datasets, emphasizing the greater accuracy of CNN-based models. Through the use of classification reports and confusion matrices, the research evaluates specificity, sensitivity, and accuracy. The outcomes demonstrate CNN's effectiveness in handling missing data, producing astounding accuracy of 99.53% for adults, 98.30% for kids, and 96.88% for teenagers. The article does note certain drawbacks, though, including the examination of non-clinical datasets, the exclusion of the influence of demographic variables, the lack of feature explanation, and the lack of ethical concerns when using ML to diagnose ASD.

The literature review explores a series of studies diagnosis of Autism Spectrum Disorder (ASD), including diverse methodology, approaches, and results. The papers reviewed here use machine learning methods such as deep learning, feature engineering, and acoustic-prosodic analysis to diagnose ASD. The many facets of ASD diagnosis are better understood thanks to these investigations.

Study	Methodology	Key Findings	Limitation
Nabila Zaman, 2021	Utilized six different approaches, including Naïve Bayes, for ASD diagnosis based on a child ASD dataset.	Naïve Bayes exhibited superior accuracy and efficiency for ASD diagnosis.	Lack of discussion on the dataset's representativeness and generalizability.
Minhazul Hasan, 2021	Employed DenseNet Machine Learning models for face picture classification in ASD identification	XGBoost, Gradient Boosting and random forest classifier showed superior performance	Limited discussions on the model's scalability and applicability beyond facial features and didn't address the potential bias or quality of the datasets used in the study.
Mengwen Liu, 2013	Investigated Early Intervention (EI) data and the potential of automated methods to locate probable ASD cases	Encouraging results regarding ASD detection in non-standard EI records, but challenges with multilingual data were not discussed.	Lack of comparison with other machine learning
C.Karpagam, 2022	Examined a dataset about autism using logistic regression.	Logistic regression model showed high performance with decreased data volume, but feature selection methods weren't extensively discussed.	Lack of comparison with other machine learning algorithms and their performance.
Surati Ningsih, 2021	Developed a mobile application for monitoring children with ASD symptoms using linear algorithm.	Focused on a practical application but didn't provide data on the application's effectiveness.	Limited information on the application's scalaility and user-friendly.
Shirajul lslam, 2020	Investigated ASD diagnosis with machine learning methods, K-NN, Naïve Bayes, SVM and Random Forest algorithms.	Proposed an online tool for early ASD diagnosis but didn't evaluate its effectiveness.	The effectiveness and usability of the proposed web tool remain uncertain.
Parikh MN, 2019	Performed nine supervised Machine learning algorithms on the ASD data in which neural network model includes.	Neural Network model exhibited superior performance but the general results was not discussed	The study lacked a detailed analysis of the impact of various personal characteristics on diagnostic accuracy.

Muhammad Shoaib Farooq, 2021	Explored different methods for ASD detection in children and adults, including the use of medical images and wearable devices.	Proposed Federated Learning as a solution for data privacy but didn't provide practical implementation details.	Limited discussion on the challenges and feasibility of implementing federated Learning in clinical settings
Mohanty,2021	Utilized various machine learning classifiers for ASD diagnosis such as SVM, KNN and Naïve Bayes,	Compared Multiple Classifiers and discussed the usage of ASDTest, a mobile-based screening tool.	No information on the ASDTest's real-world usage and performance. The study excluded toddler occurrences.
Muhammad Faiz Misman, 2021	Utilized Deep neural Network (DNN) for ASD screening in adults. Compared DNN with SVM. Implemented strategies to mitigate overfitting.	Both strategies enhanced DNN classifier performance. DNN outperformed SVM in accuracy.	Calls for the use of larger datasets to further improve DNN performance.
Purkayastha, 2021	Suggested five machine learning algorithms for identifying ASD in toddlers. Used F1 score and precision-recall for evaluation. Conducted feature engineering to reduced data dimensions.	Top-performing models included Logistic Regression, Naïve Bayes and SVM. Plans to incorporate deep learning techniques with a larger dataset.	Lacks detailed discussion on the performance of deep learning with larger datasets.
Brosh,2019	Explored automated acoustic-prosodic analysis for early ASD identification in pre-verbal toddlers. Used SVM and probabilistic neural network (PNN) classifiers.	PNN outperformed SVM with high accuracy, sensitivity and specificity. Early vocalization may hold ASD markers. More research needed with a broader sample.	Focuses on a specific aspect and needs validation with broader samples and alternative language development disorders.
Suman Raj, 2019	Investigated Machine Learning methods for ASD detection across age groups. Emphasized CNN-based models and used non-clinical ASD datasets.	CNN models showed high accuracy across age groups. Specificity, sensitivity and accuracy were impressive. Noted drawbacks include non-clinical datasets, demographic variables exclusion and lack of feature explanation.	Lacks clinical data, doesn't account for demographic variables, and requires ethical considerations.

Existing studies in ASD diagnosis using machine learning have made significant progress, but there is a compelling justification for more study. To begin, the requirement for larger and higher-quality datasets to improve machine learning model performance remains critical, necessitating more investigation in this work. Furthermore, although past research has focused on specific characteristics of ASD diagnosis, such as a person's facial features or ethnicity, this study takes a broader perspective. It uses artificial neural networks (ANN) to build models that include numerous diagnostic characteristics, providing an in-depth understanding of ASD diagnosis.

3. METHODOLOGY

The literature evaluation reveals a limited application of Deep Neural Network (DNN) principles are involved in the diagnostic process of Autism Spectrum Disorder in young children. Although deep learning concepts such as CNN have been applied to diagnose Autism Spectrum Disorder (ASD) using eye and brain images, it is important to note that these detections are typically only possible in children above the age of 5, once the brain is fully developed. Consequently, implementing diagnostic procedures for ASD after the age of 5 or later may be considered late in comparison to our research. Our study aims to predict whether a toddler is affected by ASD or not, within a timeframe of 12 to 36 months using Deep Neural Network (DNN). This early prediction allows parents and doctors to promptly address the symptoms and proceed with appropriate procedures as soon as possible. It is important to mention that many researchers who have utilized toddler data for ASD detection have relied on machine learning methodologies, which have certain limitations in terms of their effectiveness.

For the detection of Autism Spectrum Disorder (ASD) using Deep Neural Network (DNNs), the most appropriate methodology to follow would be KDD process, it is a border and inclusive process that encompasses various stages involved in knowledge discovery from data which involves data selection, data pre-processing, data mining, evaluation and deployment fig.1 explains the process in Fig. 1.

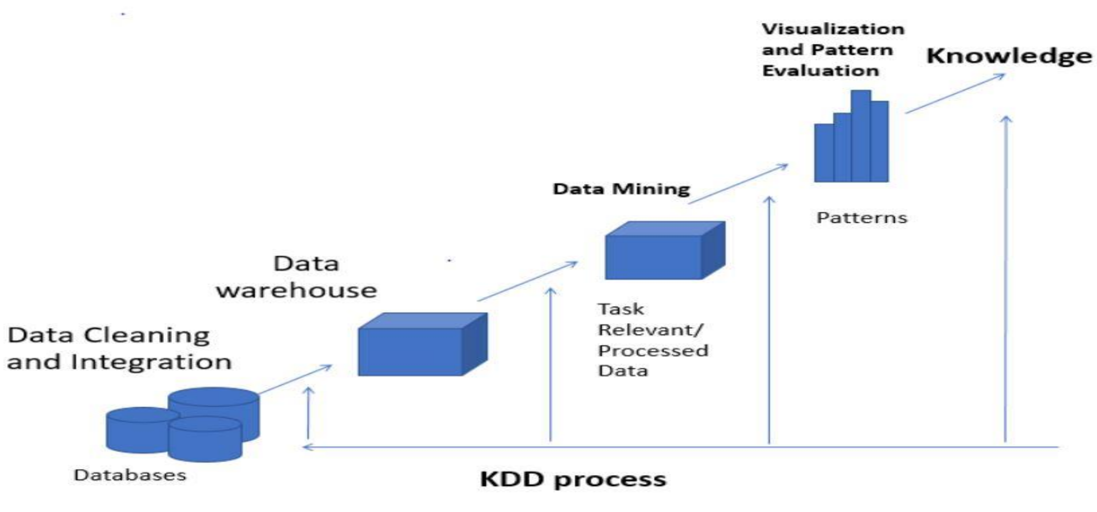

Figure1: KDD Methodology

3.1 Data Description

In our work, the dataset was deployed for the purposes of building models, training, and evaluation. The analysis includes two distinct datasets obtained from an open-access database comprising around 1757 toddlers, which were collected and provided by Dr. Fayez Thabtah. Dataset-1[1] has 1054 records of toddlers, including 19 distinct features. On the other hand, dataset-2[2] encompasses 20 features and 704 records of toddlers. These two datasets are combined together after pre-processing the datasets, the pre-processing is explained in detail below. The final dataset consists of 1757 rows and 18 columns, the detailed description of the final dataset features used in this study is mentioned in Fig. 2. In Q-Chat-10-score, if the child scores more than 3, then there is a potential ASD traits otherwise no ASD traits are observed.

Attributes	Description
A1	When you call your child's name, does he or she respond?
A2	How simple is it for you to look your youngster in the eye?
A3	Does your child make a sound or point to something when he or she wants it?
A4	Does your youngster express an interest in anything you do?
A5	Does your kid act out? Take care of dolls, for instance, or use a toy phone?
A6	Does your kid follow your lead while you're looking?
A7	Does your child exhibit symptoms of losing the desire to console someone when you or another family member is obviously upset? e.g., by embracing them or petting their hair
A8	What would you think was your child's first word
A9	Does your youngster employ basic gestures? (E.g.wave goodbye)?
A10	Does your toddler seem to be staring at nothing in particular?
Age_Mons	Age of Toddlers in Months
Qchat-10-Score	Score of the toddlers from (A1 to 10)
Sex	Male or Female
Ethnicity	The identity of a toddlers
Jaundice	Whether the case was born with jaundice
Family_Men_With_ASD	Whether any family member is affected by ASD
Class/ASD Traits	Does the toddler is affected by ASD or Not – (Yes or NO)

Figure2: Data Description

[1] https://www.kaggle.com/datasets/fabdelja/autism-screening-for-toddlers
[2] https://www.kaggle.com/code/kostaspantelidis/autism-in-toddlers/data?select=Toddler+Autism+dataset+July+2018.csv

3.2 Data Pre-Processing

In this study, the pre-processing of both datasets is conducted individually. For dataset-1, an analysis for missing values is carried out, revealing that there are no of null values. Following that, the column 'who_completed_the_test' has been removed since it is considered unnecessary. Finally, the processed dataset is saved under the name 'Dataset1'.

After conducting an in-depth analysis of the second dataset, it was discovered that there were two instances of missing values in the 'Age in months' column. To handle these null values, initially the maximum and minimum values of the dataset were examined, resulting in the identification of outliers within the 'Age in months' column. Next, the decision was made to remove the column containing the outliers. Following this, the null values were replaced with the mean value of the age variable, resulting in the absence of any remaining null values. After our next analysis of the age column, we identified an additional 10 outliers by quantile method and found maximum and minimum outliers, which were eventually eliminated from the dataset to avoid any variation in the results. Next, we performed a detailed review of the unique values involved in the categorical columns. In particular, the column labelled 'ethnicity' had the values '?', 'others', and 'Others'. To prevent any potential misunderstanding during the visual representation of the dataset, we replaced these values with 'Others'. The removal of undesired columns has been executed. Furthermore, the modified dataset was saved as 'Dataset2'.

Finally the pre-processed datasets are combined to form the final dataset ‘Combined dataset’. In the final dataset there were no null values, the unwanted column ‘Case_No’ is removed and while checking for the unique values in categorical features we found the column ‘Class/ASD Traits’ consists of 'No' 'Yes' 'NO' 'YES' so, we replaced ‘No’ with ‘NO’ and ‘Yes’ with ‘YES’. Now, the dataset is ready for visualization, model implementation and evaluation.

Prior to implementing the Model, the dataset is divided into two parts. One of them includes all the features except the target variable, which is used for training. The other part only includes the target variable. The splitting of the training and test datasets is inappropriate, which involves the utilization of one-hot encoding. As a result, the sizes of the test and training datasets have been adjusted appropriately for implementation.

4. DESIGN SPECIFICATION

The research work's architectural representation is illustrated in Figure 3. The foundation for the implementation for detecting Autism Spectrum Disorder (ASD) in toddlers is built upon well-established concepts of Knowledge Discovery in Databases (KDD).

The KDD process, also known as Knowledge Discovery in Databases, is a systematic methodology that encompasses many stages such as data preparation, data pre-processing, model construction, assessment, and deployment. The objective of this approach is to get valuable knowledge and insights from datasets by employing visualization techniques. The aforementioned approach has been employed to enhance the advancement and execution of an Artificial Neural Network (ANN) structure to assist in early detection of Autism Spectrum Disorder (ASD) in young individuals.

The employed methodology employs a multi-layered Artificial Neural Network (ANN) framework in order to detect initial indications of Autism Spectrum Disorder (ASD) in young children. ANN is neural network that has a connection with multiple neurons. Every neuron cell possesses a set of input values and corresponding weights. The most common kind of artificial neural network is the feed-forward neural network. Within this network, the transmission of information exclusively occurs in forward direction. This particular network architecture consists of three primary layers: the input layer, the hidden layer, and the output layer Fig. 3.

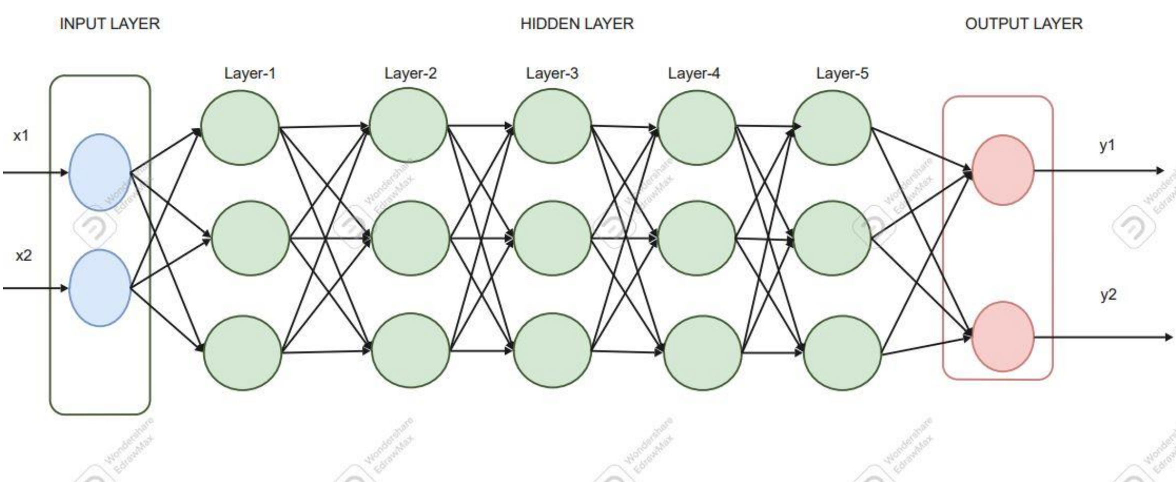

Figure 3: ANN Architecture

The architecture of the artificial neural network (ANN) is intended to effectively capture complex patterns present in input data, which is crucial for the purpose of early detection of ASD. The selection of the number of neurons in each layer, including the input, hidden, and output layers, is carefully considered to strike a balance between the complexity of the model and its ability to generalize. The input layer is responsible for handling pre-processed and normalized attributes pertaining to the behavior and development of toddlers, hence guaranteeing the provision of relevant input. The utilization of hidden layers, which incorporate Rectified Linear Unit (ReLU) activation functions, facilitates the model's ability to acquire knowledge pertaining to both linear and nonlinear interactions. The sigmoid function is employed in the output layer to provide a probability score that indicates the probability of Autism Spectrum Disorder (ASD) being present. The utilized framework is Keras, which effectively streamlines the building of neural networks by seamlessly integrating with TensorFlow, hence enabling efficient and expedited experimentation.

The effective implementation of the project requires both software and hardware requirements. In the field of software, it is essential to use Python, Keras, and relevant libraries for the purposes of data preparation and visualization.

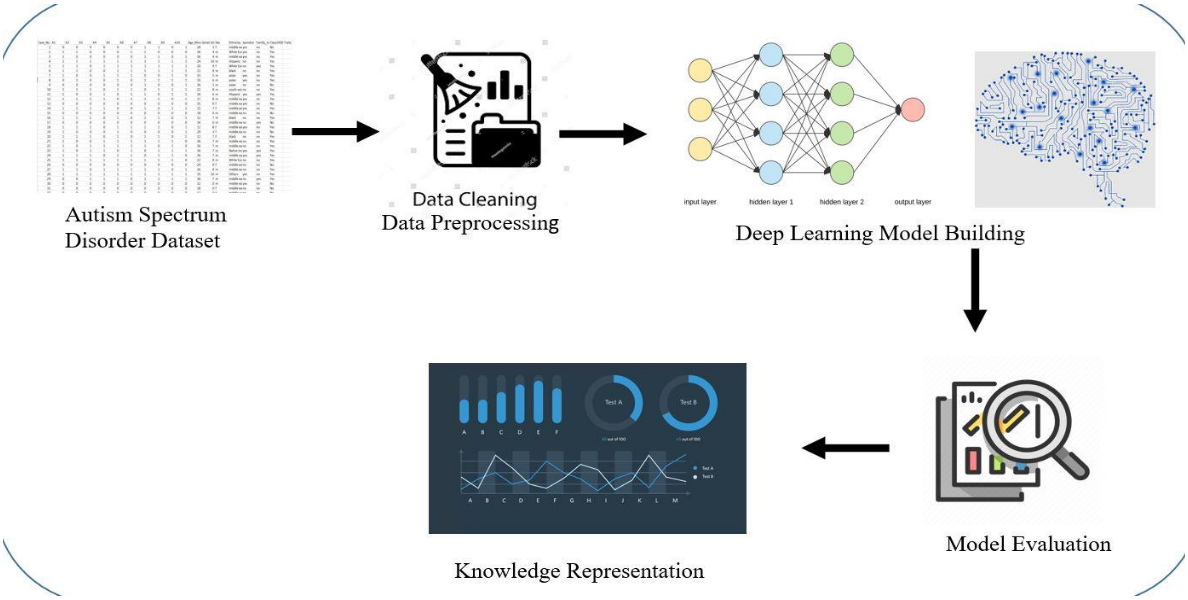

Figure 4: Framework for detection of ASD in toddlers Using Deep Learning Method

5. MODEL IMPLEMENTATION

The proposed approach involved the implementation of a neural network model to address the detection of ASD in toddlers. The model architecture was created with the Keras library. The proposed model had many densely connected layers, each with a different number of neurons. The ReLu activation function was utilized to introduce non-linearity in the model. The final output layer employed a sigmoid activation function, which is indicative of a binary classification problem which is explained in detail in design specification section. The model was developed using ANN algorithm and complied with the Adam optimizer, employing a learning rate of 0.001, and employing a binary cross-entropy loss function, the summary of the models is shown in Fig: 5. during the training process, the model was trained using a batch size of 10 for a duration of 20 epochs. In order to evaluate the improvement and efficiency of the training process, accuracy and loss metrics were gathered for both the training and validation datasets. Two different models were created in which model-1 all the variables are selected and in the model-2 except column A5, A7 and Q-chat-10-Score all other variables are selected, these columns are according to correlation plot since they are highly correlated.

The models were tuned by hyper-parameters for a better accuracy and less loss function in which we have used hyperbrand algorithm from keras tuner to search for the best hyper-

parameter to maximize validation accuracy for a neural network model. The tuner will explore different combinations of hyperparameter and training epochs to find the optimal configuration. The end results of the models were evaluated to find the performance of the model.
The complete execution procedure carried out using the Python programming language, along with necessary libraries including Keras and pandas for data processing and visualization purposes.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               4736

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 32)                2080

 dense_3 (Dense)             (None, 16)                528

 dense_4 (Dense)             (None, 8)                 136

 dense_5 (Dense)             (None, 2)                 18

=================================================================
Total params: 15,754
Trainable params: 15,754
Non-trainable params: 0
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               4352

 dense_1 (Dense)             (None, 64)                8256

 dense_2 (Dense)             (None, 32)                2080

 dense_3 (Dense)             (None, 16)                528

 dense_4 (Dense)             (None, 8)                 136

 dense_5 (Dense)             (None, 2)                 18

=================================================================
Total params: 15,370
Trainable params: 15,370
Non-trainable params: 0
```

Figure 5: Model Summary

6. EVALUATION

In the section the performance and the feasibility of the Deep Neural Network model which is implemented for the detection of Autism Spectrum Disorder (ASD) is evaluated. The model's performance is evaluated by the metrics such as accuracy, precision, recall and F1-score, in order to determine its capability in early ASD detection. The model is built with all the features for the implementation.
To understand how well the model is learning and whether it's overfitting or underfitting can be found with help of loss and accuracy curves, which is visualized using the training, validation loss and accuracy over epochs. The Loss and accuracy curve is showed below Figure. 6.

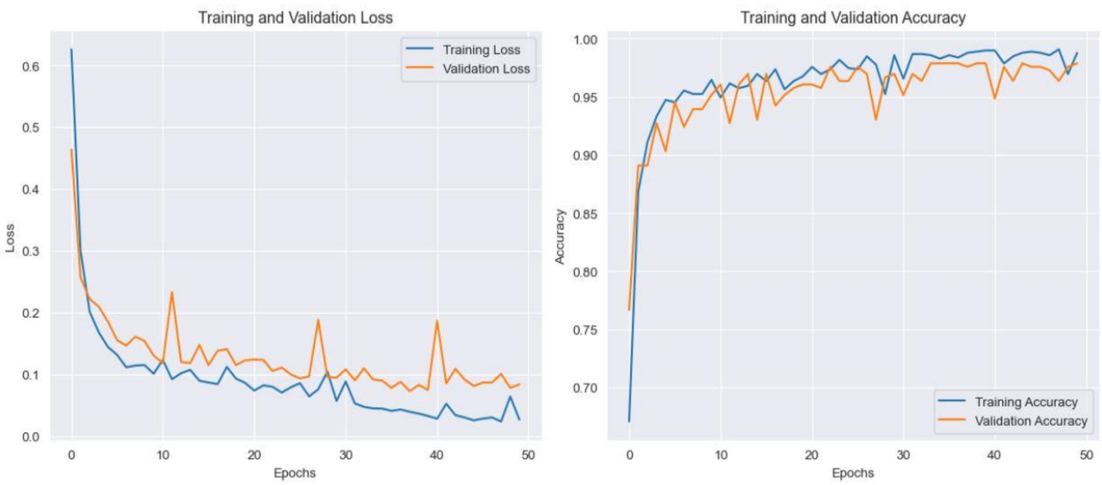

Figure6: Accuracy and Loss Curve

The loss function quantifies how far off the model's prediction are from the actual target values. From Fig: 6 the loss curve decreases, which shows that the model is learning and improving its prediction over time. The accuracy curve measures the proportion of correctly predicted instance out of the total instance, as the accuracy curve increases the model performs better at each epochs. Both the curves are important for assessing an ANN model's training progress and performance, finally the accuracy of the model is 97% and the loss of data is 0.1, which shows the model performs well.

The confusion matrix is used for better understanding of the model's performance across different classes which are follows:
True positive (TP): when the person predicted that the person would have ASD, then the person does really have ASD,

True negative (TN): the model predicted that the person did not have ASD, and it is true that the person does not have ASD,

False positive (FP): is the error in which the person is predicted with ASD but the person do not and

False negative (FN): this error predicts the person does not have ASD, but the person has ASD.

Confusion Matrix: The confusion matrix of our model is shown in fig: 7, thus Fake positive is very less and the true positive is high which depicts that the accuracy of the model will be higher with less loss of data. The classification report is calculated by the results of confusion matrix.

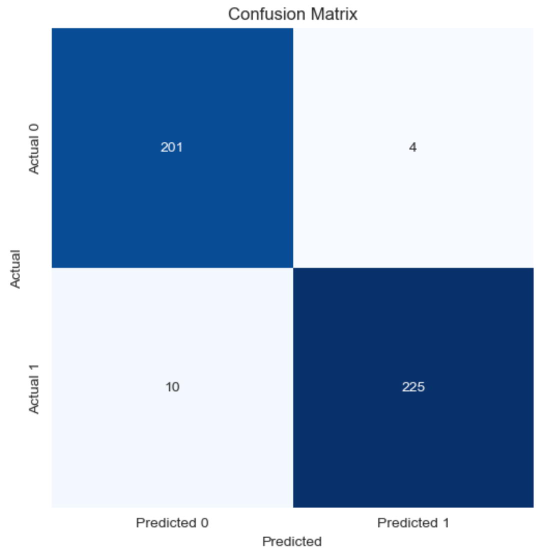

Figure7: Confusion Matrix

Accuracy: Accuracy is the proportion of accurately predicted data points in the entire dataset

Accuracy = (T P + T N) / (T P + F N + F P + T N)

Recall (Sensitivity): Recall is the percentage of correctly positive classifications (true positive) from examples that are actually positive.

Recall = TP / (TP +FN)

Precision: Precision is the percentage of correctly positive classifications (true positive) from situations that are expected to be positive.

Precision = 2 × Precision × Recall /Precision + Recall

F1 Score: The F1 score is calculated by adding Precision and Recall together. The harmonic mean is employed to determine the f1 score rather than the general mean value. As a result, both false positive and false negative observations are included in this score.

F1 score = 2* (Precision *Recall) / (precision+ Recall)

The classification report shows the metrics of precision, recall and f1-score depicts in figure.8. The precision indicates how accurate the positive prediction are for that class by which the predicted instance of our model is 95% accurate for ‘0’ and 98% accurate for ‘1’. Recall indicates that the model identifies 98% of ‘0’ are actual ‘0’ instances and 96% of instance ‘1’. F1-score is the harmonic mean of precision and recall. The ‘0’ and ‘1’ class has a 0.97 F1-score which reflects the balance between precision and recall. Support refers to the number of actual instance in each class, then the accuracy of the model is 97%.

	precision	recall	f1-score	support
0	0.95	0.98	0.97	205
1	0.98	0.96	0.97	235
accuracy			0.97	440
macro avg	0.97	0.97	0.97	440
weighted avg	0.97	0.97	0.97	440

Figure8: Classification Report

After that the model were tuned by hyper-parameters in which the hyperband algorithm is used to find the best hyper-parameters the end results were 98% accuracy and 0.08 loss, the model performance were increased after tuning the model. A comparison of the model is shown in the fig.9 in which it’s observed there is a significant change after tuning the model.

	Accuracy	Loss	Precision	Recall	F1-Score
Model-1	96.82%	0.1	95%	98%	97%
Tuned Model	98.04%	0.08	98%	95%	97%

Figure 9: Comparison between model-1 and Tuned Model

The model is evaluated by confusion matrix Fig.10 in that the TP and TN are high indicating the model works fine and classification report Fig.11 shows the overall performance of the model which is better after tuning the model.

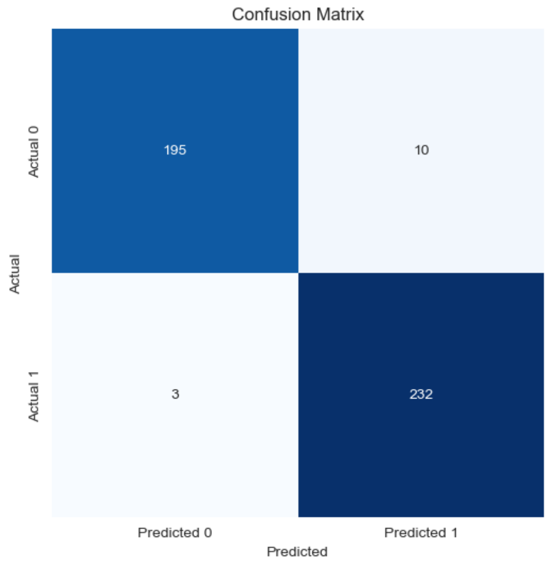

Figure: 10 Confusion Matrix

	precision	recall	f1-score	support
0	0.98	0.95	0.97	205
1	0.96	0.99	0.97	235
accuracy			0.97	440
macro avg	0.97	0.97	0.97	440
weighted avg	0.97	0.97	0.97	440

Figure: 11 Classification report

6.1 Case study -2

In this case study the model is built by selected features from the data, certain features are removed according to the correlation plot which is shown is fig: 12.

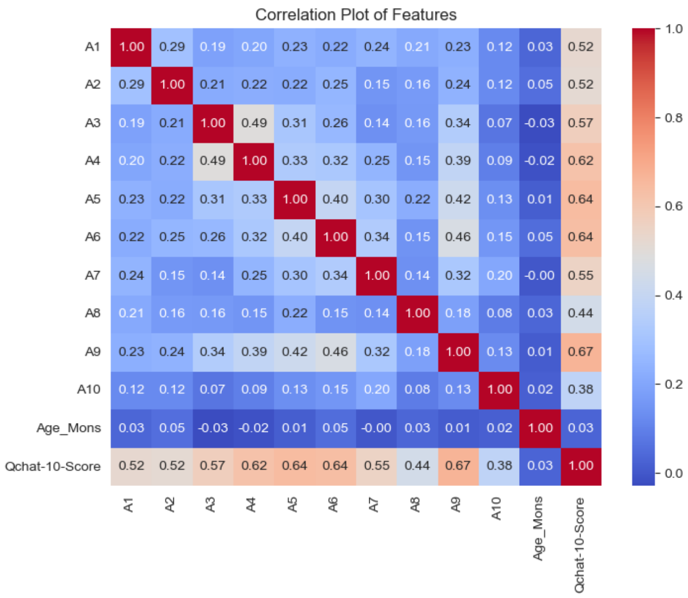

Figure12: Correlation Plot

According to the correlation plot, the columns Q-chat-10-score, A5 and A7 is removed since they are highly correlated together, after removing the columns the data is used to build the ANN model for implementation. This model is also evaluated with respect to loss and accuracy curve shown in fig: 13 as the model is trained we could notice that the curve is diverging apart due to some noise in the data or other feature issues, which may increase the loss function. On the other hand the accuracy curve increase gradually as the model is been trained which will produce satisfactory level of accuracy.

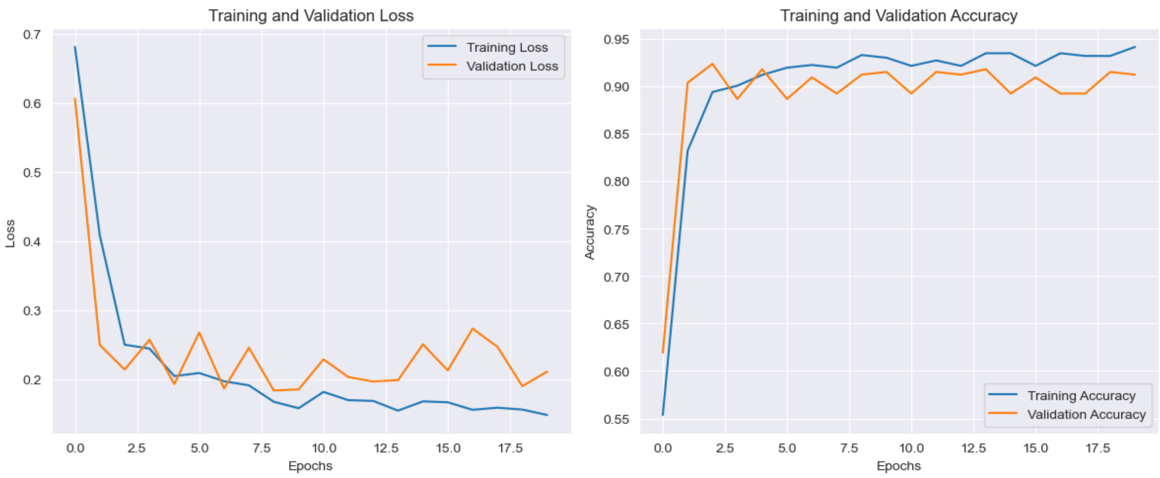

Figure13: Loss, Accuracy Curve

The confusion matrix of the second model is shown in figure.14, the fake positive (FP) and fake negative (FN) are differ by two values and then true negative is greater than true positive which clear shows the model is doing well in correctly predicting the negative class instance which is more important in while predicting a health related disorder or disease.

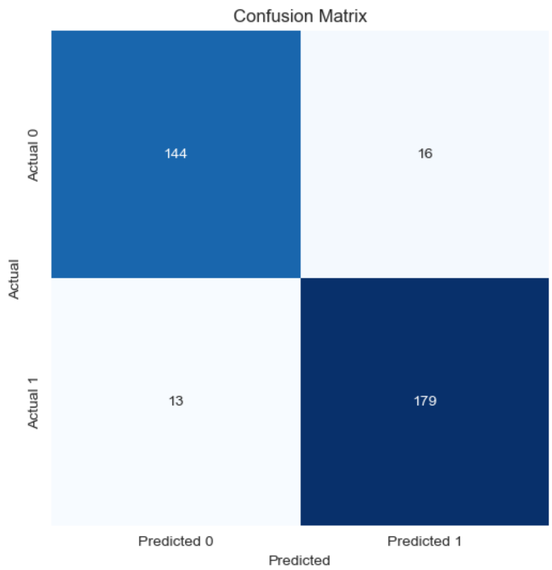

Figure14: Confusion Matrix

The classification report provides a platform to assess the model's performance on particular classes as well as overall. The accuracy was 91% , precision – 92% on classes ‘0’ and ‘1’, F1-score and recall of the model is 91% and 90% for the class’0’ and ‘1’, which shown in figure: 15.

```
              precision    recall  f1-score   support

           0       0.92      0.90      0.91       160
           1       0.92      0.93      0.93       192

    accuracy                           0.92       352
   macro avg       0.92      0.92      0.92       352
weighted avg       0.92      0.92      0.92       352
```

Figure15: Classification Report

The second model is tuned by hyper-parameter using hyperband algorithm for improving the performance of the model, after tuning the model the accuracy was increased to 3% a complete comparison between the models are shown in Fig.16, in which there is complete improved performance of the tune model.

	Accuracy	Loss	Precision	Recall	F1-Score
Model-2	91.76%	0.19	92%	90%	91%
Tuned Model-2	93.75%	0.18	96%	96%	94%

Figure 16: Comparison between model-2 and Tuned Model

The tuned model is evaluated by confusion matrix in which the false negative is reduced as compared to the un-tuned model, since the true negative is greater than true positive this model is also correctly predict the negative class instance fig.17 and classification report presents the overall report of the models performance in Fig.18.

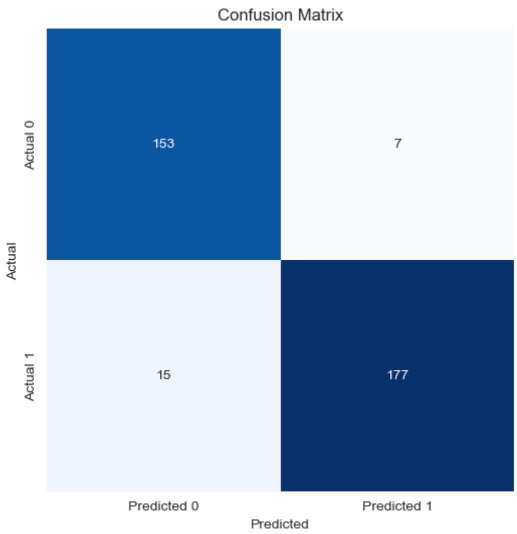

Figure 17: confusion Matrix

	precision	recall	f1-score	support
0	0.91	0.96	0.93	160
1	0.96	0.92	0.94	192
accuracy			0.94	352
macro avg	0.94	0.94	0.94	352
weighted avg	0.94	0.94	0.94	352

Figure 18: classification report

6.2 Discussion

In this section, we explore into an extensive analysis of the outcomes from two case studies conducted to evaluate the performance of the Deep Neural Network (DNN) model for detection of Autism Spectrum Disorder (ASD) in toddlers. In case study-1 all the features of the data are selected and in case study -2 some features are removed since they are highly correlated together. The models performance are examined by loss and accuracy curves, confusion matrix and classification report.

The model has good results in the first case, as evidenced by its accuracy rate of 97% and a loss function value of 0.01. The loss and accuracy curves indicate that the graph does not exhibit a significant spike as a result of the pre-processing techniques employed on the dataset prior to model installation. If the dataset is appropriately cleaned, then the model is going to continue to show excellent results throughout the training process. The model is tuned using hyper-parameters of hyperband algorithm which improved the performance of the model, the accuracy was increased by 1%. If there is large records of ASD data then the tuning the model by hyper-parameters may reflect a significant improvement in the performance of the model.

In the second case study, several features from the dataset are excluded based on the correlation plot due to their close correlation with one another. The final outcomes of the model did not meet the performance of the previous model. By examining the loss and accuracy curve, we observed a sudden spike, suggesting the presence of noise in the data or other features. However, the model shows effectiveness in accurately predicting instances of the negative class, as evidenced by the confusion matrix. Given the limited availability of data related to the prediction of Autism Spectrum Disorder (ASD) in toddlers, the current model demonstrates good accuracy. In this model, after hyper-parameter tuning the models performance increased by 3%, the end accuracy was 94%.

When an enormous amount of data regarding Autism Spectrum Disorder (ASD) in toddlers becomes available, the model's performance can be significantly enhanced. The outcomes derived from the model can then be utilized to develop an application or website. To refine the model's performance, it is necessary to adjust hyperparameter and make use of pre-trained algorithms

7. CONCLUSION AND FUTURE WORKS

The objective of this study is to implement a supervised Deep-learning technique utilizing an Artificial Neural Network with the ASD toddler dataset in order to develop an ANN model capable of distinguishing between ASD and NON-ASD instances.

But before implementing the model, the two datasets undergone pre-processing. The first dataset was cleansed by removing unnecessary columns, rendering it suitable for the model's building. The second dataset offered challenges in data pre-processing due to the presence of missing values, outliers, and unwanted columns. Specifically, the column 'Age in months' contained both missing values and outliers. Since the objective of the study was to detect Autism Spectrum Disorder (ASD) in toddlers aged below 36 months and to ensure consistency and accuracy in the results, these missing values and outliers were removed. The column labelled "ethnicity" had various entries such as 'others', 'Others', and '?'. These entries were then updated with the standardized term 'Others', and the datasets were accordingly stored. Following that, the two datasets were merged to create the ultimate dataset utilized for developing the model. This dataset included 1757 instances of children diagnosed with Autism Spectrum Disorder (ASD), comprising 18 distinct attributes. The datasets included in this study were released in 2017 and 2018, therefore indicating a limited amount of previous work or research conducted with these datasets. This suggested model has the potential to be utilized as a foundation for future research projects connected to these datasets. Then the model was well-developed using Artificial Neural Network (ANN) and produced a good classification result in classifying ASD in toddlers with the given features of the patient's medical information.

Overall the proposed model performed well in classifying toddlers ASD and proven to be significant. The model was successfully developed utilizing Artificial Neural Network (ANN) and achieved a good result in accurately diagnosing Autism Spectrum Disorder (ASD) in toddlers based on the provided patient medical data after that the models were tuned by hyper-parameters by which the performance of the model was improved . In overall, the proposed model performed good performance in accurately diagnosing toddlers with Autism Spectrum Disorder (ASD) and demonstrated statistical significance.

However, it is highly recommended to use a more massive dataset to enhance the efficacy of the artificial neural network (ANN) model. Additionally, utilizing hyperparameter is crucial to assert the accuracy of the model and ensure proper classification of the data, reducing the potential issue of overfitting. I would propose to take account of other features, such as parental age, since it has been seen in a study (Mohanty, 2021) that children born to older parents are more likely to possess Autism Spectrum Disorder (ASD). Furthermore, it would be beneficial to investigate the relationship between the parents, specifically if they are cousins, as offspring born to close relatives have a greater chance of developing ASD.

Finally, the enhanced model might be deployed within an application or utilized to construct a website. Consequently, when parents input relevant information related to their children, they will have the capability to ascertain the possibility of the kids being diagnosed with Autism Spectrum Disorder (ASD) or not.

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