AUTICHECK: AN ASD SCREENING TOOL FOR TODDLERS USING CONVOLUTIONAL NEURAL NETWORKS

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In Partial Fulfillment

of the Requirements for the Degree

Bachelor of Science in Computer Science

by

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Approval Sheet

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Abstract

Autism Spectrum Disorder (ASD) is a condition characterized by significant challenges in social interaction, communication, and behavior, stemming from neurological development differences. Diagnosis typically involves lengthy and costly procedures conducted by specialized professionals in clinical settings. Self-administered and parent-administered screening tools have been developed to help recognize autistic traits in the preliminary stage such as the QCHAT-10. However, the accuracy and efficiency of these screening methods rely primarily on the experience and knowledge of the user, as well as the items designed in the screening method. To enhance the accuracy, sensitivity, specificity, and efficiency of the screening tool, a promising solutions is to build classification systems using machine learning and deep learning. The research introduces AutiCheck, a screening tool designed for toddlers aged 24-36 months to detect Autism Spectrum Disorder (ASD). AutiCheck integrates Convolutional Neural Networks (CNN) with the conventional screening tool Q-CHAT 10, trained on a dataset containing

1054 screening results from Kaggle. The tool achieved impressive metrics, with an accuracy of 99.33%, sensitivity of 99.31%, and specificity of 99.38%. Furthermore, the system was evaluated according to the ISO/IEC 25010 standard, receiving positive ratings for all eight assessed characteristics, indicating high quality and effectiveness in meeting user needs. This proposed system shows potential in identifying ASD traits in toddlers, potentially assisting parents and guardians in making decisions regarding seeking a formal diagnosis from a doctor.

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CHAPTER 1 INTRODUCTION TO THE STUDY

Background of the Study

A neurodevelopmental impairment known as autism spectrum disorder (ASD) can cause serious social, communicative, and behavioral difficulties. The term "spectrum" describes the vast array of abilities, symptoms, and degrees of impairment that people with ASD may display. While social interaction difficulties are common symptoms among people with ASD, there are differences in the timing, severity, quantity, and the presence of additional conditions of these symptoms. Additionally, symptoms and their severity can evolve over time (NIDCD, 2020).

The “Autism Diagnostic Observation Schedule” or “ADOS” and the “Autism Diagnostic Interview-Revised” or “ADI-R” are two commonly used diagnostic tools for autism. The “ADI-R” is an interview with a semi-structured format that is used to gather information on a child's behavior and developmental history from parents or other caregivers. The ADOS is an observation-based test that assesses a child's socialization, play, and communication abilities in a controlled environment. These tools are considered the gold standard for diagnosing autism and are typically used in conjunction with clinical observation and evaluation by a qualified healthcare professional (Ali et al., 2019).

While the mental and physical health of the person being evaluated depends on an early identification of ASD, the formal diagnosis process might take a long time because of the consensus coding, scoring, training, and administration requirements (Thabtah et al, 2019). Self-administered and parent-administered screening methods have been developed to help recognize autistic traits in the preliminary stage. Examples include the "Screening Tool for Autism and Toddlers and Young Children (STAT)", "Childhood Autism Rating Scale (CARS-2)", "Modified Checklist for Autism in Toddlers (M-CHAT)", "Quantitative Checklist for Autism in Toddlers (Q-CHAT)", and "Autism Spectrum Quotient (AQ)(Child, Adolescent, and Adult version)". These screening tools help parents, caregivers, and medical professionals determine whether a patient needs a complete diagnostic assessment. They are typically provided in the form of a questionnaire. The limitations of these screening tools however, is that the the accuracy of the resulting classifications relies heavily on three factors: (1) the design of the questionnaire items themselves, (2) the expertise of the administrator conducting the screening, and (3) the objectivity and validity of the handcrafted rules embedded within the scoring function. It takes considerable knowledge and expertise to design the rules that will be used to calculate the scores of the questionnaire's components. Substituting human-derived rules with knowledge extracted from previous cases and controls to enhance diagnostic outcomes and classification processes seems beneficial. Unlike handcrafted human rules, automated knowledge is not subjective because they are discovered using advanced learning approaches such as machine learning (ML) or data mining, and consequently, boosting specificity, sensitivity, and predictive accuracy as well as classification efficiency. These intelligent methods must be utilized by clinicians, parents, teachers, caregivers, and family members, among others, to improve the outcome of the screening. Furthermore, clinicians can use this information to validate screening results based on their own expertise and experience (Thabtah & Peebles, 2020).

Deep learning is an artificial intelligence (AI) technique that trains computers to comprehend data in a way that is similar to the human brain. Deep learning models are able to create accurate analyses and forecasts by recognizing complex patterns in text, audio, picture, and other kinds of data (AWS, 2023). Among the most well-known and often used deep learning (DL) networks is the convolutional neural network (CNN) (Alzubaidi et al., 2021). CNN is a subclass of neural networks that focuses on handling data with a grid-like architecture, such as (but not limited to) images (Mishra, 2020). By incorporating DL techniques into the screening tool, the predictive quality in detecting the likelihood of ASD will improve.

Theoretical Framework

Baron-Cohen et al. (1992), stated that key psychological predictors of autism can occur in as early as 18 months. These are manifested by the presence of two or more of the following characteristics at 18 months: (a) absence of imaginative play, (b) absence of proto-declarative pointing, (c) absence of social interest, (d) absence of social play, and (e) absence of joint attention.

Parents, caregivers, and healthcare professionals, including family physicians and general practitioners, who are often the primary individuals approached by parents expressing concerns about potential autism-related behaviors, require screening tools that assist them in identifying these early warning signs. According to Allison et al. (2012), these signs may act as clues to ask them to send the child for a thorough diagnostic assessment.

Categorizing all the data elements or features into two separate categories falls under a type of classification problem known as "binary classification" (Jeatrakul & Wong, 2009). Rahman et al. (2020) state that the fundamental requirements for employing machine learning techniques for classification can be outlined as follows:

1. Preprocessing stage:

   (i) Feature selection: Choose relevant features.

   (ii) Data preprocessing: Employ techniques to reduce noise, handle missing values, and balance the dataset through sampling.

2. Classification stage (core steps):

   (i) Input: Utilize a designated dataset containing both control and positive ASD cases.

   (ii) Procedure: Develop a predictive model for diagnosing ASD by integrating machine learning classification algorithms into diagnostic tools.

   (iii) Output: Generate a predictive model capable of determining the class for test data.

Considering that the objective of this study involves determining the classification of toddlers as either having a risk of ASD or not, the methodologies outlined by Rahman et al. (2020) are relevant to the aims of this study.

As shown in Figure 1, By incorporating artificial intelligence such as deep learning into the screening tools, we can identify risk of autism in toddlers early and achieve higher accuracy.

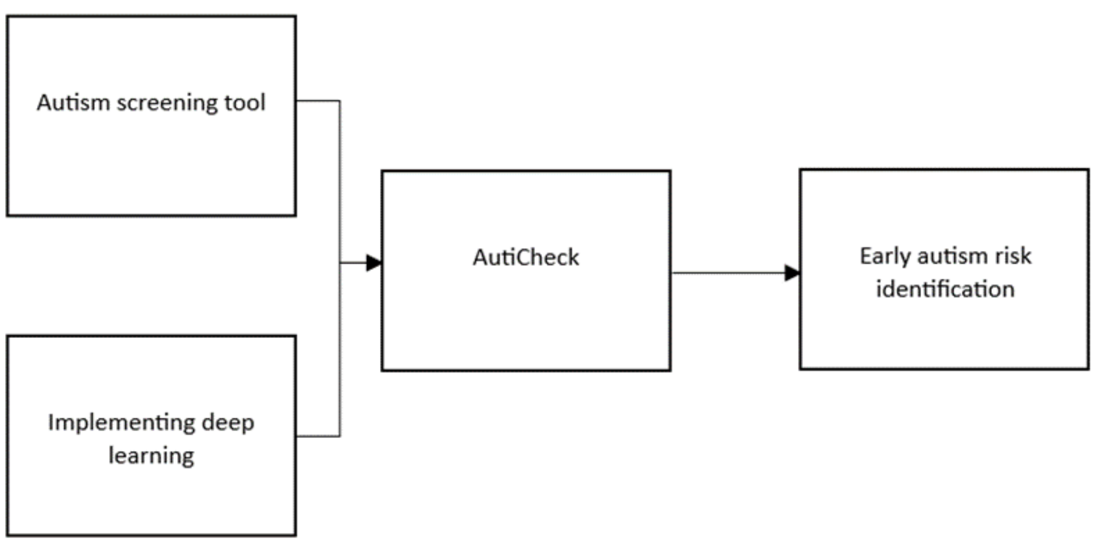

Figure 1. The theoretical diagram of the proposed study

Objectives of the Study

This study aims to develop Auticheck: An ASD screening tool for toddlers using covolutional neural networks.

Specifically, this study aims to:

1. Train and implement the CNN algorithm as a model for detecting the likelihood of ASD,
2. Evaluate the model's specificity, sensitivity, and accuracy,
3. Incorporate the proposed screening tool into a Web Application,
4. Evaluate the system based on the characteristics defined in ISO/IEC 25010.

Significance of the Study

The study will be beneficial to the following:

Individuals with ASD.

The results for people with ASD can be improved by early discovery and intervention, and this study can assist in early case identification. This may result in prompt support services and interventions that can raise the person's quality of life.

Parents and caregivers.

This study can aid in raising parents' and caregivers' knowledge of ASD symptoms and indicators. By using the application, they can learn more about the condition and its effects on behavior, communication, and social interaction.

Healthcare professionals.

This study’s web-based application can be accessible and convenient for healthcare professionals to use, as they can easily access it from their devices. This can increase the availability of autism screening and diagnosis, especially in areas where there is a shortage of healthcare professionals.

Teachers.

With knowledge of a child's ASD diagnosis, teachers can adjust their teaching strategies to better meet the child's needs. This may involve modifying the curriculum, providing additional support, or using alternative teaching methods.

Researchers.

The data generated from this study can help researchers better understand ASD, including its prevalence, risk factors, and potential treatments. This may result in a better comprehension of ASD and the creation of more potent remedies.

Definition of Terms

For better understanding, the following terms were defined conceptually and operationally:

Autism Spectrum Disorder (ASD)

According to Zigebaum et al. (2019), ASD is a chronic neurodevelopmental disorder characterized by unusual interests or sensitivities, constrained, repetitive behavioral patterns, and difficulties connecting with others.

In this study, the convolution neural network will be used to identify and classify ASD as a medical disease.

Toddler

A child is commonly referred to as a toddler from around 12 months old until they are approximately 3 years old. The word "toddle" refers to a youngster who is still learning to walk, hence the term "toddler" (Corley, 2022).

In this study, toddlers starting from ages 18-36 months are the subject for the identification of ASD traits.

Web Application

A web application is a type of computer program that is hosted on a remote server and accessed by users through a web browser. This software has several benefits because it can be used on various types of computers and operating systems as long as a browser is available (Volle, A.).

In this study, a web application will be developed as a tool for screening ASD.

Screening Tool

Screening tools are intended to detect the possible existence of a particular problem (ScienceDirect, 2023). The main goals of ASD screening instruments are to determine the probability of ASD and offer a preliminary assessment of whether additional testing is required. While screening tools can help identify potential ASD symptoms, they are not designed to provide a definitive diagnosis or specify the level of ASD severity (NCBDDD, 2022). Determining the level of ASD severity typically requires a comprehensive evaluation conducted by qualified professionals.

In this study, the screening tool to be used is the “Quantitative Checklist for Autism in Toddlers” or “Q-CHAT-10”.

Quantitative Checklist for Autism in Toddlers (Q-CHAT-10)

The “Q-CHAT-10” is a toddler ASD screening tool. The questionnaire consists of ten questions on the child's behavior, which the authors Allison et al. (2012) identify as symptoms of ASD. While the recommended toddler age to use Q-CHAT-10 is from 18-24 months, multiple studies have shown that it can be extended until the 36^{th} month.

In this study, this is the screening tool adopted for the development of the web application.

Artificial Intelligence (AI).

Artificial intelligence (AI), as defined by 'Introduction to AI' (n.d.), is the pursuit within computer science aimed at constructing intelligent computers capable of executing tasks that typically necessitate human intelligence.

In this study, AI is going to be used in AutiCheck's Q-CHAT-10 to achieve better accuracy, sensitivity, and specificity.

Deep Learning

Deep learning is a subset of machine learning that uses neural networks with three or more layers. Even though they fall well short of the human brain's capacities, these neural networks attempt to mimic its functions and enable it to "learn" from enormous amounts of data (IBM, 2023).

In this study, a deep learning model is employed to the web application to improve its accuracy to classify ASD and learn from the data it receives.

Algorithm

An algorithm refers to a clear and precise set of instructions that aim to solve a specific problem. The algorithm takes a set of input(s) and produces a desired output as a result (*What Is an Algorithm?*, n.d.).

In this study, algorithm is defined as the computational procedure utilized for analysis and classification.

Convolutional neural network (CNN)

A subgroup of deep learning networks known as convolutional neural networks employs many artificial neural network types to manage various data types and applications (Awati, 2022).

In this study, CNN is the deep learning algorithm that will be used to develop our model.

Delimitation of the Study

The "Q-CHAT 10" is a screening tool designed to help parents and caregivers recognize the symptoms of autism in children; it is not a diagnostic tool for ASD. Rather, it serves as a referral for healthcare professionals such as psychologists or developmental pediatricians to conduct a formal diagnosis of ASD through a series of interviews and observations.

Based on the data used in the study, the age of the toddlers will only range from 18 to 36 months.

This study, only being a screening tool, will not specify the level of ASD severity of the toddler and will only be predicting the likelihood of an autism trait in a toddler.

The study will focus on improving the accuracy, specificity, and sensitivity of the Q-CHAT 10 by incorporating artificial intelligence. In contrast to the traditional method of scoring it, which is based on human-defined rules, this process of improvement will be achieved by using a CNN deep learning algorithm to learn new insights and patterns from the Q-CHAT 10 dataset. The end result will be a more dependable artificial intelligence-based scoring system.

Chapter 2 REVIEW OF RELATED STUDIES

Autism Spectrum Disorder

ASD is a neurodevelopmental disorder brought on by irregularities in the brain that show up as restricted or repetitive hobbies and routines, difficulties interacting with others, and difficulties speaking and interacting socially. Furthermore, learning, movement, and attention patterns may differ in those with ASD. While some people without ASD may exhibit similar symptoms, it's crucial to remember that these traits can make daily life particularly difficult for those who have the illness.

Although the precise causes of ASD remain unclear, research points to a potential interaction between hereditary and environmental factors. People's genes may interact with their environment to impact their development and increase their chances of having ASD. ASD risk factors include having an older parent, having a sibling with ASD, and having specific genetic abnormalities including fragile X syndrome or Down syndrome. Furthermore, extremely low birth weight may potentially play a role in the development of ASD.

Autism in children must be diagnosed using a two-step process. The first phase involves a comprehensive evaluation of the child's development by a pediatric professional. If any concerns are identified during this evaluation, then the child must undergo further examination. A more thorough assessment is carried out in the second stage by medical specialists with a variety of specializations. At this point, the kid might be diagnosed with a developmental disability other than ASD. The "Autism Diagnostic Observation Schedule" and the "Autism Diagnostic Interview-Revised" are the standard instruments for the diagnosis of autism. A kid with ASD can typically be accurately diagnosed at two years old, while some evaluations indicate that the illness can be detected as early as 18 months. Psychiatric diagnostic classifications state that signs of autism should manifest before to the age of three. However, because the symptoms over the first two years are nonspecific, early diagnosis is difficult (Ali et al., 2019).

Thus, early and accurate diagnosis of Autism Spectrum Disorder (ASD) is crucial for providing appropriate interventions and support to individuals with ASD. Despite the difficulties in getting an early diagnosis due to the lack of distinguishing indicators in the initial two years of life, attempts have been made to identify ASD as early as 18 months of age. For those with ASD, early intervention and support may dramatically boost outcomes, underscoring the significance of a prompt and precise diagnosis.

Conventional Methods of Screening ASD in Toddlers

Experts in psychology, behavioral science, and psychiatric health have created self-administered and parent-administered screening tools to assist parents, caregivers, and medical professionals in identifying early signs of autism. These tools can help people spot the early warning symptoms of autism in other people.

One of the earliest validated screening tests for autism, the "CHAT" (Baron-Cohen et al., 1992), initially demonstrated potential for screening at 18 months of age due to a high contemporaneous "positive predictive value

(PPV). However, following a 6-year follow-up, the 18-month CHAT identified just 38% of the children that eventually were diagnosed with autism. Because of the CHAT's low sensitivity and the need to remove the kid observation components, the screening tool was modified to become the "Modified CHAT (M-CHAT)" (Robins, 2008). This updated version also included parent report items. Another modified version of the “CHAT” and “M-CHAT”, called the “Quantitative Checklist for Autism in Toddlers” or “Q-CHAT” (Allison et al., 2008), replaced the binary (yes/no) responses with ordinal (how much/often). The purpose of this was to acknowledge the existence of autistic features on a spectrum or dimension.

Subsequently, Robins et al. (2014) created the M-CHAT-R (Revised), a standardized follow-up interview for positive screens that is conducted by clinicians. In primary care settings, the follow-up interview is not as frequently used. Younger toddlers had a lower “PPV” of the “M-CHAT-R” than older toddlers, even with the follow-up interview.

Allison et al. (2012) aimed to shorten the 25-item Q-CHAT. The researchers selected the 10 best items on the instrument and then evaluated the accuracy of this shorter version in identifying individuals with ASD. The findings demonstrated that the shortened Q-CHAT was useful in distinguishing between those with ASD and those without, with good sensitivity and specificity at different cut points. The study suggests that this shorter version has the potential to aid frontline health professionals in making referral decisions for specialist assessment for ASD.

Sturner et al. (2022) conducted a comparative analysis between the "Q-CHAT-10" and "M-CHAT". This study evaluated both positive and negative-screened children, which may have contributed to the two-stage "M-CHAT-R/F" screening method's poorer sensitivity for diagnosing autism than previously reported. In comparison to "M-CHAT-R" and "M-CHAT-R/F", the "Q-CHAT-10" screening approach performed better in terms of sensitivity, specificity, and the number of items needed. However, its positive predictive value was still relatively low, meaning that most children who were screened positive would not be confirmed to have autism. It is possible to recommend the "Q-CHAT-10-O" version for ASD screening at 18 months because it doesn't involve a follow-up interview and uses the entire range of responses for each item. However, more research is required to increase its positive predictive value.

Deep Learning and Machine Learning for the Classification of ASD

Using automated methods like support vector machines, rule-based classifiers, decision trees, neural networks, and decision trees, the emerging field of machine learning aims to produce accurate predictive models from research datasets. Specialists use these tools to diagnose autism spectrum disorder by training them on input data sets and evaluating their performance on test cases. Various software packages include different machine learning algorithms, such as ‘Weka’, ‘R’, ‘scikit-learn’, and the ‘MATLAB toolbox’ (Rahman et al., 2020).

Using machine learning models, forward feature selection, under-sampling, and 10-fold cross-validation, Duda et al. (Duda et al., 2016) trained and tested six models on complete Social Responsiveness Scale score sheets from 2925 individuals with ASD or ADHD. They found that five of the 65 behaviors measured by this screening tool were enough to distinguish between ASD and ADHD with high accuracy (area under the curve = 0.965). These results indicate that machine learning can accurately differentiate between autism and ADHD using a small number of commonly measured behaviors. The findings show that it has the potential to be used as a caregiver-directed resource for preliminary risk evaluation, pre-clinical screening, and triage, which could speed up the diagnosis of these disorders.

Bi et al. (2018) discovered that low accuracy was obtained while classifying ASD patients and "typical controls (TC)" using a single "Support Vector Machine (SVM)". They employed a number of SVMs and resting-state fMRI data from 46 TC and 61 ASD patients in the Autism Brain Imaging Data Exchange (ABIDE) database to address issue. It was then suggested to use the "random SVM cluster" approach to differentiate between 'TC' and ASD. Based on all features, the results demonstrated that this method performed exceptionally well in terms of classification, with an accuracy of 96.15% when using the best feature set. Additionally, abnormalities were found in the 'hippocampus, precuneus, and inferior frontal gyrus (IFG)'. This shows that the supplemental diagnosis of ASD may benefit from the random SVM cluster technique.

Vaishali & Sasikala (2018) used a dataset from the UCI machine learning repository that included 21 features related to ASD diagnosis. They applied a swarm intelligence-based binary firefly feature selection wrapper to identify the minimum set of features needed to accurately distinguish between ASD and non-ASD patients. They found that using 10 features out of the 21 in the dataset was sufficient to achieve a high classification accuracy, with an average accuracy between 92.12% and 97.95% using the optimized feature subsets. The notion that machine learning models can attain high accuracy with a smaller set of features is supported by this outcome.

Thabtah and Peebles (2020) developed a new machine learning method called Rules-Machine Learning, which not only detects autistic traits of cases and controls but also offers users knowledge bases (rules) that can be utilized by domain experts in understanding the reasons behind the classification. The predictive accuracy, sensitivity, harmonic mean, and specificity of Rules-Machine Learning were compared with those of other machine learning techniques, including Boosting, Bagging, decision trees, and rule induction, using three datasets pertaining to children, adolescents, and adults. The outcomes demonstrated that, in comparison to alternative methods, Rules-Machine Learning provided classifiers with superior levels of specificity, harmonic mean, sensitivity, and predictive accuracy.

Researchers like Shahamiri and Thabtah (Shahamiri et al., 2020) and Achenie et al. (Achenie et al., 2019) have also investigated deep learning techniques. Based on their answers to the M-CHAT-R screening tool, Achenie et al.classified toddlers as having autism spectrum disorder (ASD) or not using the feedforward neural network (fNN) technique. The study analyzed data from 14,995 toddlers aged 16–30 months and found that the best-performing models achieved high accuracy in classifying ASD, ranging from 99.64% to 99.92%, depending on the subgroup analyzed (i.e., race, sex, and maternal education). The study suggests that the fNN technique could be used as a tool for preliminary risk evaluation and pre-clinical screening to speed up the diagnosis of ASD.

Shahamiri and Thabtah (Shahamiri et al., 2020) utilized the convolutional neural networks that were trained using an extensive autism dataset. The dataset included cases and controls of autism across various age groups, such as adults, adolescents, children, and toddlers. The outcomes produced by the CNN were then contrasted with results from alternative intelligent algorithms. Notably, the CNN showcased superior performance, particularly in the proposed ASD classification system, where it exhibited higher levels of accuracy, sensitivity, and specificity compared to conventional screening methods.

With superior results as reported in the study of Shamiri and Thabtah (Shahamiri et al., 2020), we are going to explore a deep learning technique, specifically convolutional neural networks, to identify ASD risk in toddlers. By leveraging the superior results achieved by CNNs in the previous study, we seek to harness the power of deep learning techniques to create a new screening tool for toddlers. With their ability to extract intricate patterns and features from complex data, CNNs offer a promising avenue for accurately identifying and classifying ASD traits in this specific age group.

Existing Screening Applications for Autism

Existing Applications	Age Group/s	Additional Information
ASDTests (mobile application)	toddler, child, adolescent, and adult	• Available in 11 languages • Initially collected over 1400 cases and controlsl
ASDetect (mobile application)	11 to 30-month-old child	• Includes narrated videos by the author, demonstrating key social-communication behaviors comparing autistic, and non-autistic, children. • According to its developers, the app is 83% accurate in identifying early signs of autism.
Awesomely (mobile application)	child, adolescent, adn adult	• Uses the traditional AQ screening questionnaire. • Available in various languages and has a rating of 4.1, with 54 reviews and over 10,000 downloads
Autism AI (mobile application)	toddler, child, adolescent, and adult	• Uses a CNN that has been trained with historical ASD cases to classify new cases.

Table 1. *Summary of screening applications*

Thabtah (Thabtah, 2019) introduced a new mobile application called ASDTests that provides a user-friendly, efficient, and accessible autism spectrum disorder screening tool for individuals and the health community. Health practitioners can use this app to help with their practice and to counsel patients about whether to get a formal clinical diagnosis. As an alternative to other autism screening applications already on the market, ASDTests offers four tests—one for each age group—and is accessible in eleven different languages. This allows it to reach a larger audience. The app is also an essential tool for data collection related to ASD, with over 1400 cases and controls initially collected.

Barbaro and Yaari (Barbaro et al., 2020) developed ASDetect, a free mobile application that can be accessed globally on Android and Apple platforms. It is designed to help parents assess their 11- to 30-month-old child's likelihood of autism using the early behavioral markers of autism identified in the SACS. The app includes narrated videos by the author, demonstrating key social-communication behaviors at 12, 18, and 24 months of age, comparing autistic, and non-autistic, children. This makes it an early detection and educational tool for parents. According to its developers, the app is 83% accurate in identifying early signs of autism.

Awesomely is a mobile app that features a multiple-choice questionnaire designed to screen for autism. Its primary purpose is to provide a straightforward screening tool for autism, that can be used by general practitioners to refer patients for further evaluation using the traditional AQ screening questionnaire. The app is also available in various languages and has a rating of 4.1, with 54 reviews and over 10,000 downloads (Awesomely Autistic Test - Apps on Google Play, n.d.).

In 2020, Shahamiri and Thabtah developed Autism AI, a mobile application with a user interface for gathering data from questionnaires, an intelligent web service for detecting ASD, and a database that can be used to learn new information from users of the system in the future. The application uses a Convolutional Neural Network (CNN) that has been trained with historical ASD cases to classify new cases. A sizable autism dataset with cases and controls of all ages was used to assess the CNN's performance and compare it to that of more sophisticated algorithms.

Hence, while various applications have already been developed, we plan to contribute to this field by developing an application that can be localized to our language and culture and provide a tailored experience for users in the Philippine context.

Convolutional Neural Network (CNN)

For image identification and classification applications, “convolutional neural networks” or “CNNs” have gained popularity (Krizhevsky et al., 2012). CNNs are a type of deep learning algorithm that can extract and learn relevant features from large datasets. LeCun, Bengio, and Hinton (LeCun et al., 2015) stated that they are composed of many filter layers that employ convolutions on the input data, succeeded by pooling layers that diminish the dimensionality of the feature maps.

Although the CNN architecture of deep neural networks accepts a sample as an image, it is possible to leverage the power of CNNs for non-image data such as textual and tabular data. By adopting appropriate data preprocessing techniques and architectural modifications, CNNs can effectively analyze and extract meaningful features from these non-image data types.

This method is discussed in the novel research of Sharma et al. (Sharma et al., 2019). According to them, a wide range of data, including genomic, transcriptomic, methylation, mutation, text, spoken words, financial, and banking data, exists in non-image forms. Machine learning techniques have been extensively applied in these fields, demonstrating their effectiveness. However, CNNs have traditionally been used for image data, as they typically require images as inputs. Nevertheless, if we can transform non-image data into a well-organized image format, CNNs can be leveraged to achieve higher classification performance.

The goal of Xin et al.'s (Xin et al., 2019) study was to create deep learning classifiers that would use clinical data to identify sepsis early. They combined models of “recurrent neural networks (RNNs)” and “convolutional neural networks (CNNs)”. They came to the conclusion that, when applied to real-world datasets containing randomly missing data and unequal class distributions, neural network techniques might be more effectively used to forecast sepsis.

Poudyal et al. (Poudyal et al., 2022) also utilized CNN for prediction using a tabular dataset. Their study involved the development of a hybrid 2D (CNN) model for predicting academic performance. Despite having 1D data as their sample, they transformed it into 2D image data to assess the performance of their hybrid model. The researchers compared the performance of their model with various traditional baseline models, including k-nearest neighbor, naïve Bayes, decision trees, and logistic regression. Their hybrid 2D CNN model demonstrated superior accuracy compared to the baseline models.

Therefore, CNN can definitely be explored forto use for classification tasks because of its ability to extract and learn relevant features from data, regardless of whether it is image, textual, or tabular data. By adapting the data preprocessing techniques and making architectural modifications, CNNs can be effectively applied to non-image data, such as textual and tabular data. This opens up new possibilities for utilizing CNNs in various domains, including genomics, finance, healthcare, and academic performance prediction. The studies mentioned demonstrate the potential of CNNs in these areas, showcasing their ability to achieve higher classification performance and improve prediction accuracy compared to traditional baseline models.

ASD is difficult to diagnose, thus early detection is essential. To aid with early identification, a number of screening tools have been developed, including the "CHAT," "M-CHAT," and "Q-CHAT," which have all seen improvements in sensitivity and specificity. Using a variety of methods, including ‘rule-based classifiers’, ‘neural networks’, and ‘support vector machines’, machine learning has demonstrated promise in the correct classification of people with ASD. To improve the Q-CHAT 10 screening tool's ‘sensitivity, specificity, and accuracy’ in identifying children at risk for ASD, we will use CNN to simulate artificial intelligence in this study.

Chapter 3 RESEARCH DESIGN AND METHODOLOGY

Description of the Proposed Study

Our study entitled "AutiCheck: An ASD Screening Tool for Toddlers Using Convolutional Neural Networks", aims to develop a web-based screening tool for toddlers using Convolutional Neural Networks for detecting the likelihood of ASD in toddlers. The goal of the study is to create a trustworthy ASD screening tool that parents, guardians, or medical professionals can use to determine whether a kid needs a comprehensive diagnostic evaluation for ASD. Our goal is to help individuals with ASD through early detection and intervention, leading to improved outcomes and a better quality of life.

Methods and Proposed Enhancements

Preparation

Consultation Domain Expert

The study requires consultation with a specialist in neurodevelopmental disorders such as ASD. Dr. Celina C. Gellada, a licensed Pediatrician, was selected as the consultant. During our discussion, we consulted regarding the dataset to be utilized and the validity of the Q-CHAT 10 screening tool. Furthermore, we explored examples that could facilitate accurate responses from the users, such as shown in Table 2.

Table 2. Examples for Questions 1 and 2

Question	**Example**
*1.*Does your child look at you when you call his/her name?	a.)You're in the same room as your child, and you say, "Sarah!" Does Sarah turn her head and make eye contact with you?
	b.) While engaged in an activity together, you say, 'Sarah!' to get your child's attention. Does Sarah pause what she is doing, shift her focus to you, and make eye contact within a reasonable timeframe?
2.How easy is it for you to get eye contact with your child?	a.) When you're talking to or playing with your child, how easy is it for you to make and maintain eye contact? Does your child look at your face during interactions?
	b.) When you intentionally look at your child's face, does he /she reciprocates by making eye contact with you and sustaining it for at least a few seconds?

Data Acquisition

The dataset that will be used for this study was obtained from Kaggle (www.kaggle.com/datasets/fabdelja /autism-screening-for-toddlers). It consists of 1054 screening data points for toddlers using Q-CHAT 10. Table 3 shows the list of attributes in the dataset.

Table 3. *List of attributes in the dataset*

Attribute ID	Attribute Description
1	Case Number
2	Sex
3	Age of toddler in months
4	Ethnicity
5	The patient suffered from Jaundice problem by birth
6	Any family member with ASD
7	Who is completing the test
8-17	Answer to 10 questions on the Q-CHAT 10
18	Qchat-10-Score
19	Label (ASD or non-ASD)

Implementation

Data Preprocessing

To ensure the quality, consistency, and usefulness of the raw data for the desired analysis, data preparation include modifying and cleaning the data. Enhancing the data's integrity by eliminating any extraneous information, dealing with missing values, and formatting the data so that it is appropriate for the selected machine learning algorithms are the objectives (Raj & Masood, 2020).

In our dataset, there were no missing values. Feature selection, however, was made by identifying the relevant features or variables from the dataset that contribute significantly to our research. Certain columns, such as 'Who completed the test', 'Qchat-10-Score', and 'Jaundice', are dropped manually as they are not relevant for our analysis.

Furthermore, categorical variables in the dataset were encoded using label encoding. To handle the age variable, 'Age_Mons', it was binned into categories to transform the continuous age values into discrete categories, simplifying the analysis. The categorical variables "Sex," "Ethnicity," and "Family_mem_with_ASD" underwent one-hot encoding. Each category variable was thus converted into a collection of binary columns that represented the various categories.

Additionally, CNN is designed to process samples in the form of images. Therefore, the feature data, consisting of the encoded categorical variables and numerical variables, was reshaped specifically for the convolutional neural network (CNN) architecture. The reshaping process involved converting the feature data into 3D tensors to accommodate the image-based structure required by the CNN. After reshaping, the data was normalized to ensure that each feature in the input data has a similar range of values, which aids in the convergence of the CNN during training. The normalized feature data was then fed into the CNN model, allowing it to effectively learn from the input features.

Designing the CNN Architecture

Python was used as the primary programming language to create the model, and libraries like Tensorflow , Scikit-learn, and Keras were used. The development environment used for data preprocessing, model training, and testing was a Jupyter Notebook using Visual Studio Code.

The input to the CNN prediction algorithm is the preprocessed data that includes user responses to the ten behavioral questions, participant age in months, sex, and any ASD history in the family.

The grid search technique was used to determine the optimal values of the model's hyperparameters, including the number of 1D CNN layers and filters, max pooling size, number of dense layers and related filters, dropout rate, and optimizer. In machine learning, grid search is a technique for fine-tuning hyperparameters with the goal of finding the best combination for a model. It works by carefully going over a preset grid of possible values for every hyperparameter (Dremio, 2023). The grid's parameters include convolutional and dense neurons set at values of

32, 64, and 128, as well as the determination of the number of layers to be utilized, which can be either one or two. Additionally, it considers the activation function, which can take values of relu or sigmoid, the dropout rate with values of 0.3, 0.4, and 0.5, and the pool size with options of 2, 3, and 4. The hyperparameters with the best performance are shown in Figure 2. This CNN is composed of two max pooling layers, two 64-filter dense layers with activation relu and 30% dropout layer each, two 32-filter convolutional layers, and one single neuron with activation sigmoid in the final dense layer.

Training and Testing

The preprocessed dataset was split into 70% for training and 30% for testing. The number of epochs was set to 1000, with an early stopping callback configured with a value of 10. This allows training to halt immediately if the model stops improving. Early stopping was triggered, halting training at 31 epochs, as the model had reached its optimal state and stopped improving.

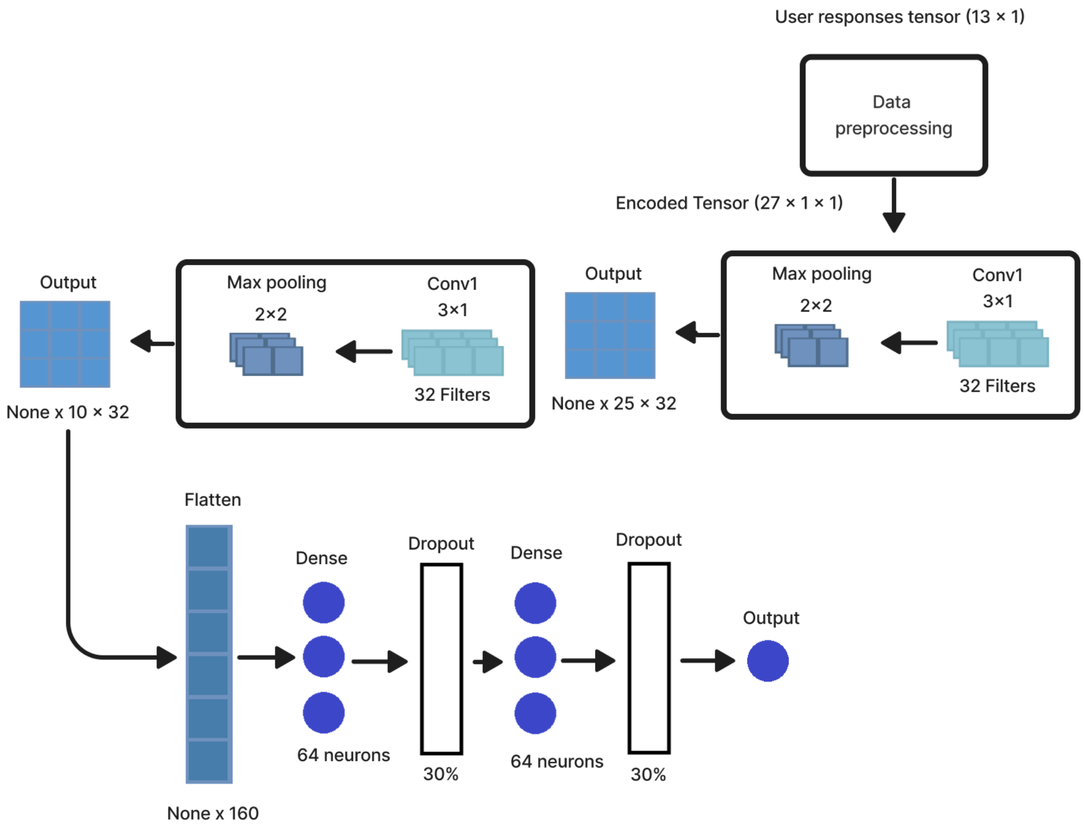

Figure 2. *The CNN Architecture*

Web Application Development

The backend was created with Python as the main language, utilizing libraries like TensorFlow and Keras for model training and loading. For the frontend, HTML, JavaScript, and Tailwind were employed for styling. Flask was used to develop the server-side components of the web applications.

Evaluation

Evaluating the Model

Analyzing how many test cases the deep learning model correctly or incorrectly predicted is one way to evaluate its performance. The confusion matrix offers a more detailed overview that not only reveals the model's predictive capabilities, but also identifies which categories are being predicted accurately or inaccurately, and what kind of errors are occurring (Liu, 2022). The following formulas are used to find the performance metrics:

Specificity = $T\mathrm{N}/(T\mathrm{N}+T\mathrm{P})$

True Positive Rate or Sensitivity = $T\mathrm{N}/(\mathrm{TN}+\mathrm{FN})$

Accuracy = $T\mathrm{P}+\mathrm{TN}/(\mathrm{TN}+\mathrm{TP}+\mathrm{FP}+\mathrm{FN})$

Additionally, cross-validation is a commonly used technique to evaluate the performance of machine learning models, including deep learning models, especially when the dataset is limited. It uses several divisions of the data to give a more accurate evaluation of the model's capacity for generalization.

The dataset is split up into many subsets, or "folds," for cross-validation purposes. The model is trained and assessed several times, using each fold as a test set and the remaining folds for training. This process allows for a comprehensive evaluation of the model's performance across different data subsets (Lyashenko, 2023).

Evaluating the System

The extent to which a system satisfies the explicit and implicit needs of its various stakeholders and so adds value is referred to as its quality. The quality model, which divides the product quality into characteristics and sub-characteristics, accurately represents the needs of those stakeholders (functionality, performance, security, maintainability, etc.).

The eight quality factors listed in Figure 3 make up the product quality model described in ISO/IEC 25010.

Figure 3. *Definition of the Software Product Quality Model in ISO/IEC 25010*

Components and Design

System Architecture

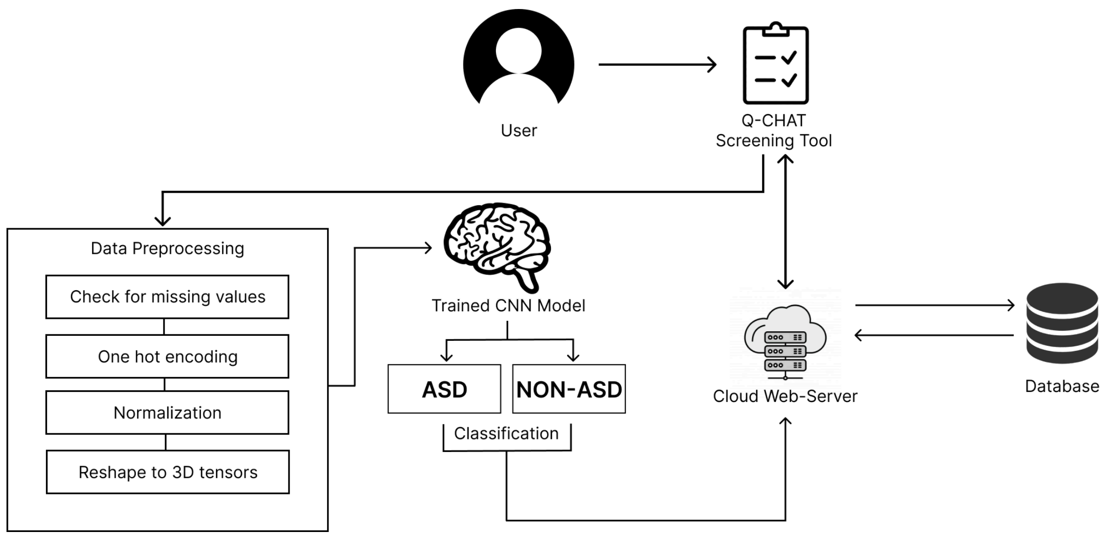

Figure 4. *System Architecture of the Proposed System*

Figure 4 outlines the system architecture of the proposed system. The diagram illustrates the key components and interactions within the system. It begins with user input through the screening tool in the app front-end. Then the input data undergoes data preprocessing including checking of missing values, one-hot encoding, normalization, and reshaping into 3D tensors, ensuring its suitability for the model.

Check for missing values: Involves checking if there are any missing values in the input data and handling them appropriately.

One hot encoding: Converts categorical data into a numerical representation.

Normalization: Scales the numerical data to a standard range.

Reshape to 3D Tensors: Prepares the data for input into a convolutional neural network (CNN) model.

Then, the preprocessed data is fed into the trained CNN model which can identify the likelihood of ASD and Non-ASD. The results are then transmitted to a cloud web server and data is stored in the database.

Database Design

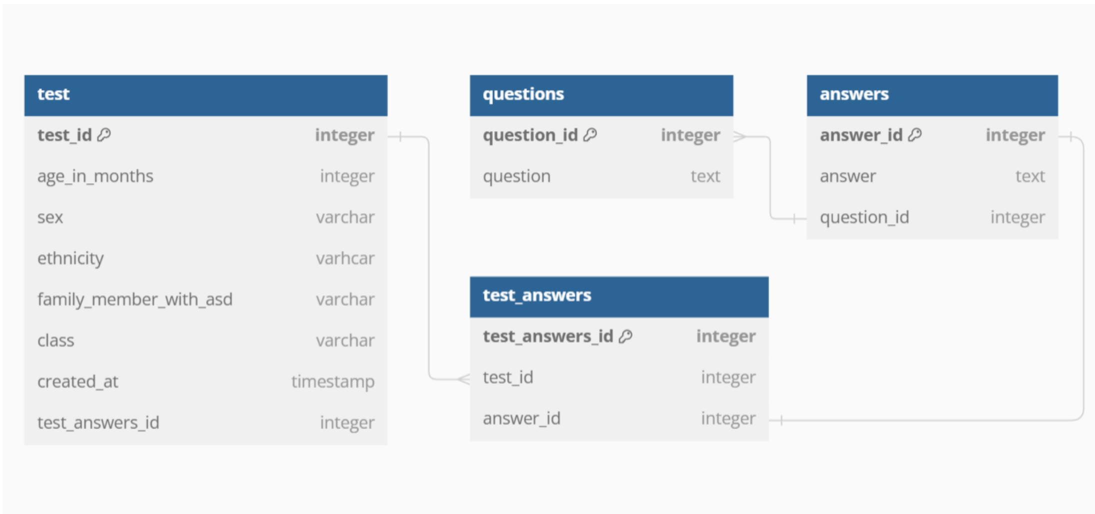

Figure 5. *Database Design of the Proposed System*

The database design shown in Figure 5 consists of four primary tables: test, questions, answers, and test_answers. The 'test' table contains detailed information about administered tests, including the toddler's age in months, sex, ethnicity, family history of ASD, test classification, test date, and a unique 'test_id' serving as a reference for the 'test_answers' table. The 'questions' table stores identifiers and questions from the Q-CHAT 10 questionnaire, while the 'answers' table holds corresponding answers alongside unique identifiers. Relationships between questions and answers are established through the 'question_id'. The 'test_answers' table acts as an intermediary, linking 'test_id' with 'answer_id' to associate specific test instances with their respective answers. This schema facilitates comprehensive data storage and retrieval for test administration and analysis.

Procedural and Object-Oriented Design

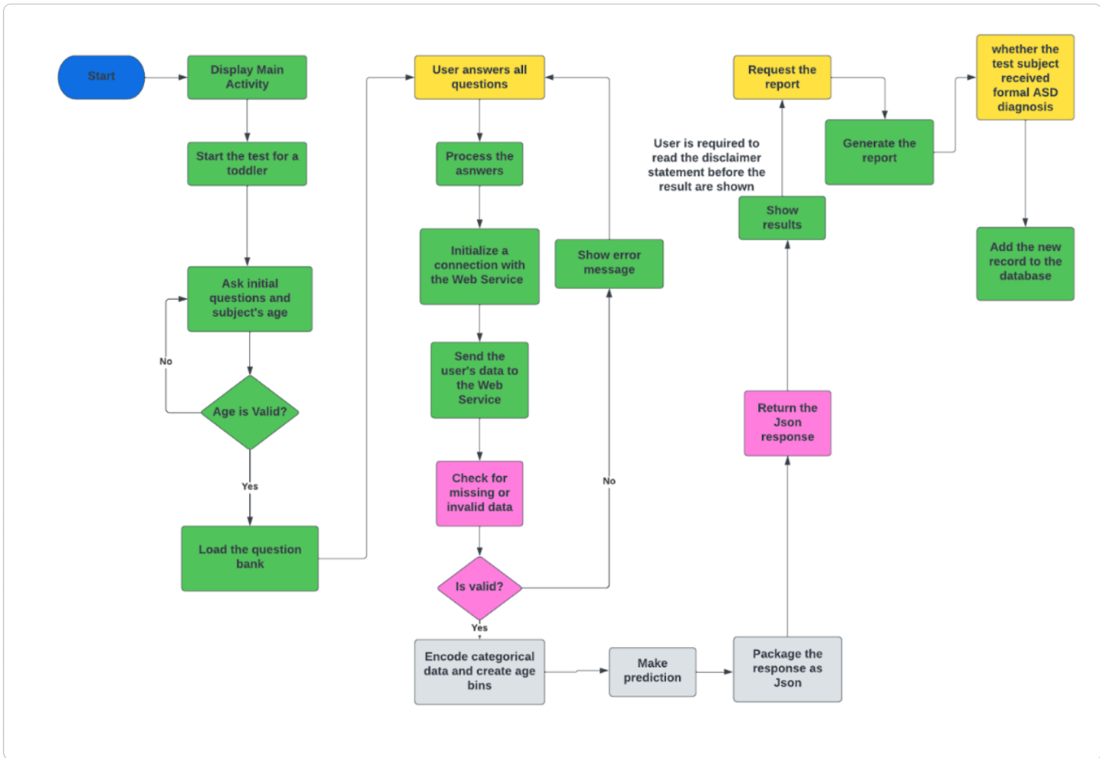

Figure 6. *Procedural and Object-Oriented Design of the Proposed System*

AutiCheck works as depicted in Figure 6. Upon opening the application, users are presented with the main page and prompted to select the age (in months) of the toddler. If an invalid age is entered, the initial questions are repeated until a valid age is provided. If the age of the toddler is valid, users will answer a set of initial questions.

Next, users will answer Q-CHAT 10. The backend checks for any missing or invalid values and displays an error message if necessary. Otherwise, the data is sent to a trained model to identify the likelihood of ASD in the toddler. Before viewing the results, users are prompted to read a disclaimer statement. The interface then displays whether the subject is likely to have ASD and if a formal diagnosis is recommended.

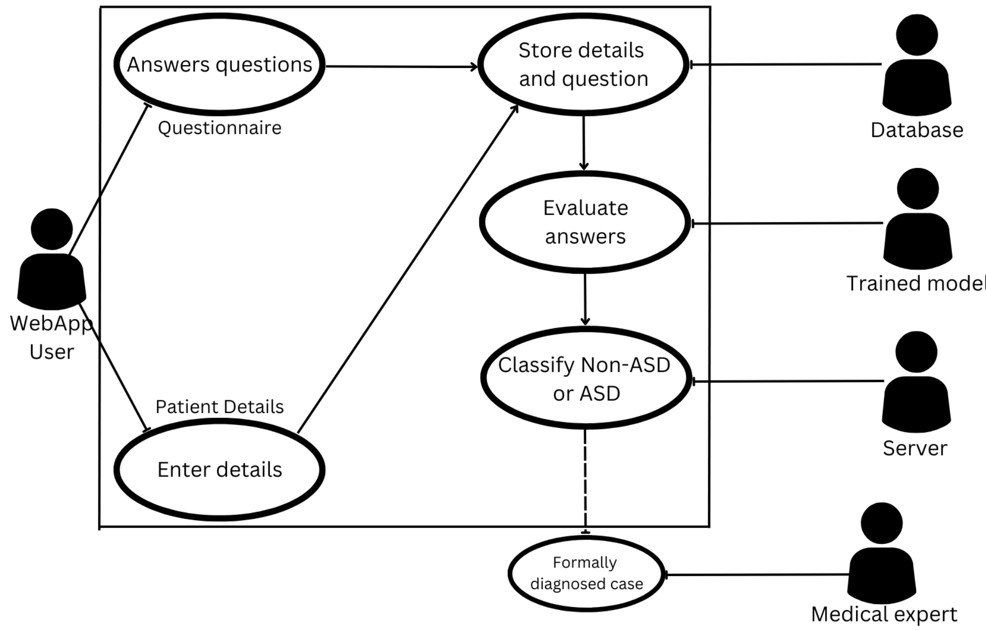

Figure 7. Use Case Diagram *of the Proposed System*

Figure 7 illustrates the use case diagram of the proposed system, depicting the various interactions between system components and actors. The primary actors include a Web App User who could be a parents or guardians, that interact with the system through the user interface, and a Medical Expert, who provides expert diagnosis and feedback. The main functionality of the system involves the Web App User answering questions through the Questionnaire, providing Patient Details, and entering relevant information. This data is then stored in a Database and used to evaluate answers, which involves identifying likelihood of ASD using the trained CNN model. A server is responsible for handling communication and processing between different parts of the system. Additionally, the classification result is used to determine a formal diagnosis, the parent or guardian can reach out to a Medical Expert for further assessment of the toddler with a suspected case of ASD.

Process Design

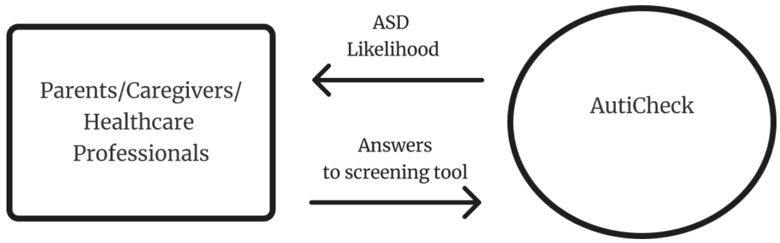

Figure 8. Context Diagram

The Context Diagram data flow diagram, as depicted in Figure 8, offers an overview of the external entities. In this scenario, these entities could be parents, caregivers, or health care professionals who interact with the system's primary functionality by inputting answers to screening questions in which AutiCheck processes the information inputted as part of the screening process and receiving an output result from the system.

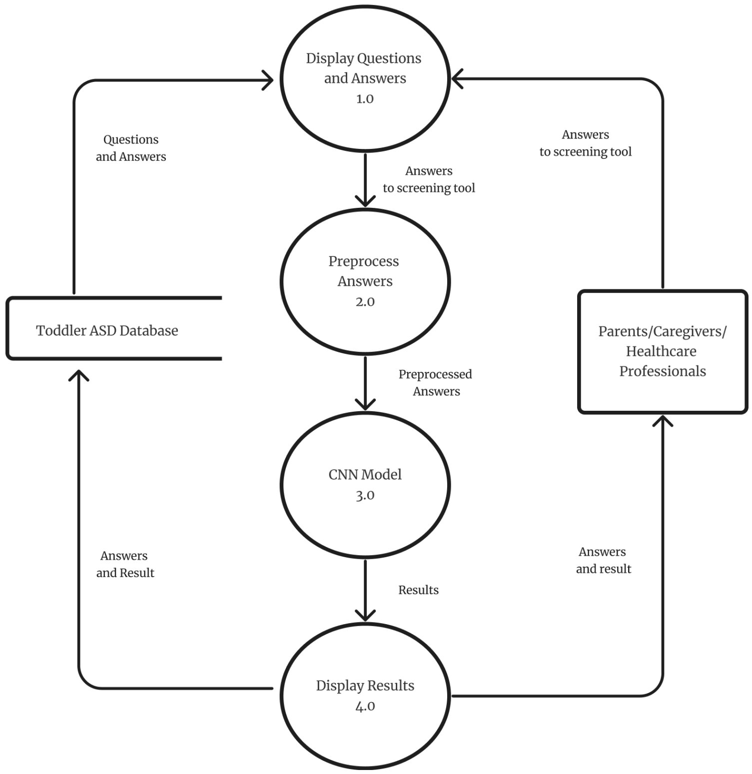

Figure 9. Level 0 Data Flow Diagram

The Level 0 data flow diagram, illustrated in Figure 9, offers a more detailed breakdown of the system processes. Initially, questions and answers are retrieved from the database and displayed to users. Upon answering a screening tool, the responses undergo preprocessing before being transmitted to the CNN model for ASD likelihood identification. Once the model generates a result,the server manages this outcome by storing both the answers and result data in the database. Finally, the user interface displays this information to the user.

Figure 10. Level 1 Data Flow Diagram for Input Validation

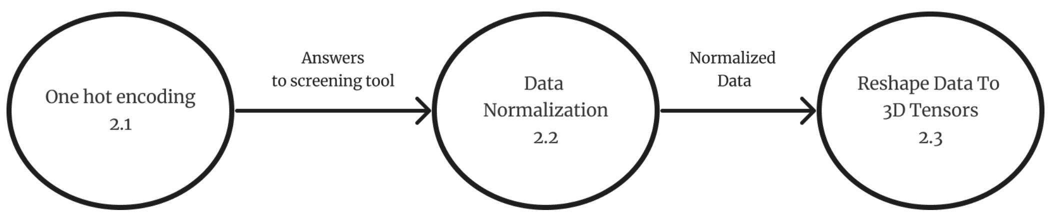

Figure 11. Level 1 Data Flow Diagram for Data Preprocessing

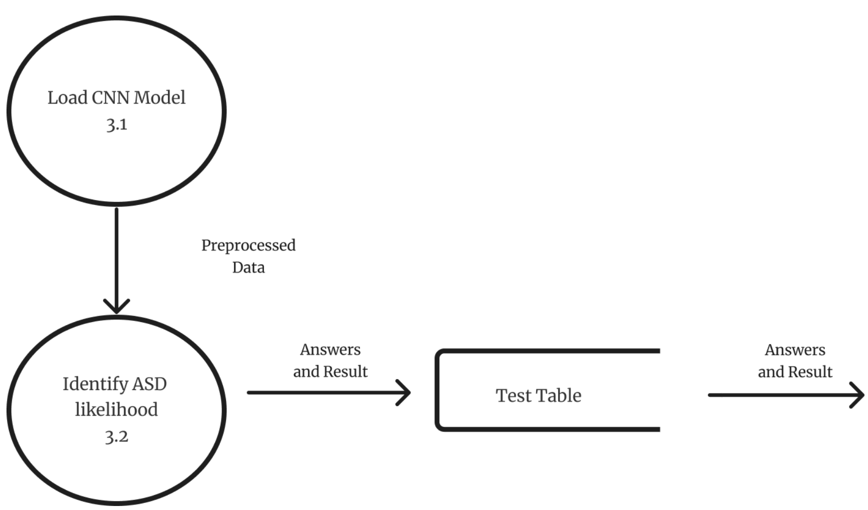

Figure 12. Level 1 Data Flow Diagram for Classification

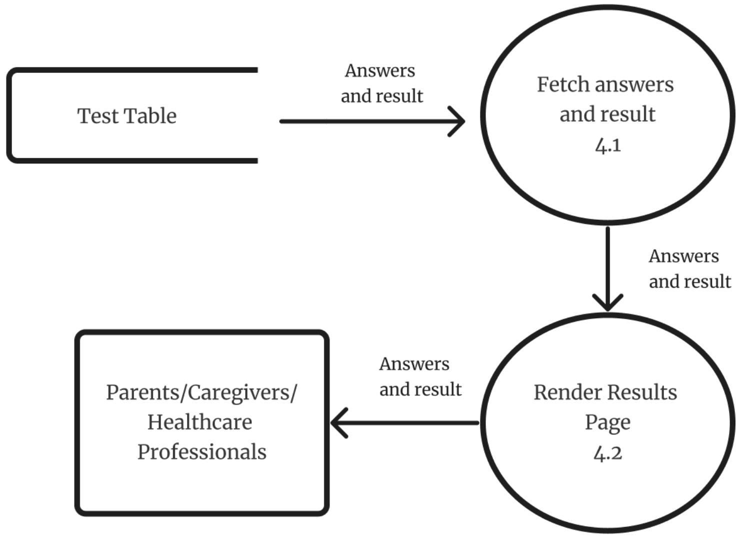

Figure 13. Level 1 Data Flow Diagram for displaying results

The Level 1 data flow diagram, presented in Figures 10 through 13, provides a detailed breakdown of the system's operations. In Figure 10, the process starts with the retrieval of questions and answers from the "questions" and "answers" tables in the database. Subsequently, this data is displayed in the user interface. The system then conducts a check for unanswered fields by the user. If any fields are missing, they are presented to the user for completion; otherwise, the request is submitted to the server via POST.

Figure 11 illustrates the preprocessing phase. Here, the data undergoes one-hot encoding, normalization, and reshaping into 3D tensors to align with the requirements of the CNN model. In Figure 12, the CNN model is loaded, followed by the assessment of ASD likelihood based on the user's answers. The system then stores both the answers and the test results in the "test" table.

Finally, Figure 13 decomposes the subprocess 4. Here, the system retrieves answers and results from the test table, afterwards rendering the results page to display the outcome to the user.

System Development Life Cycle

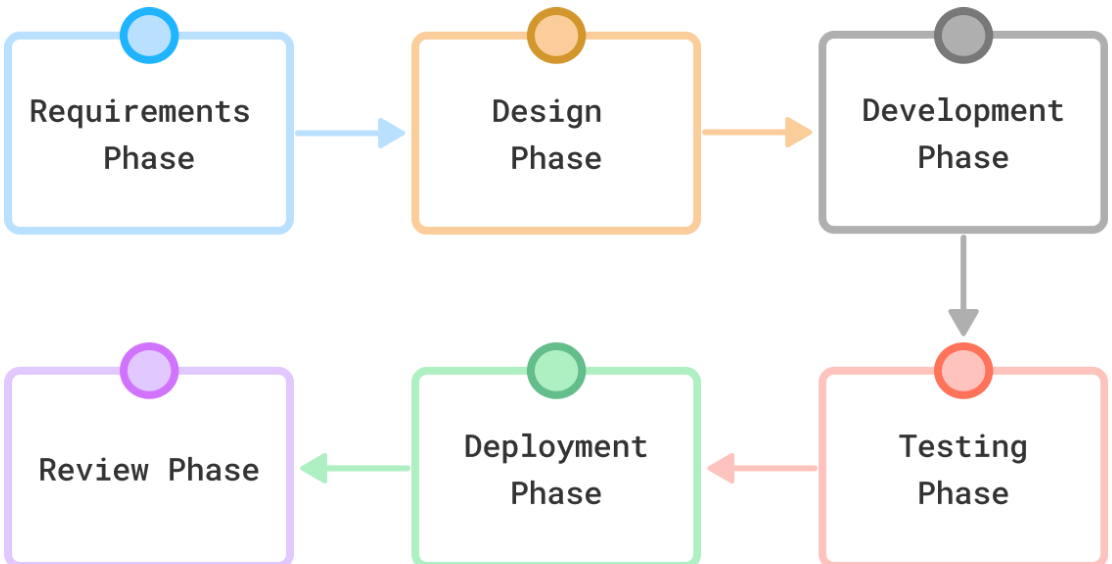

Figure 14. SDLC of the Proposed System

The researchers will follow the Software Development Life Cycle as illustrated in Figure 14: Agile Model. The agile model design consists of 6 phases: requirements, design, development, testing, deployment, and review.

Requirements Phase: In this phase, the requirements for the web application screening tool, AutiCheck will be gathered and defined in an iterative manner. This includes discussing and understanding the purpose of the system, the target users, and their needs. It will also involve defining the features, functionalities, and performance requirements of AutiCheck.

Design Phase: In this phase, the system will be designed based on the identified requirements gathered in the first phase. This will include developing a prototype to visualize the UI design, database design, detailed architectural and design plan that outlines the technical specifications, system interfaces, and other important aspects of the software.

Development Phase: In this phase, the development team will begin writing code for AutiCheck based on the design specifications in an iterative and incremental manner. This will involve building the software's core features, as well as its user interface and backend infrastructure.

Testing Phase: In this phase, AutiCheck will undergo various testing processes to ensure that it functions properly and meets the specified requirements such as quality and functionality of the software. Researchers will perform tests to validate user interactions, input validations, data handling and other functional aspects and verify that the system performs as intended.

Deployment Phase: In this phase, web application screening tool, AutiCheck will be deployed into a production environment and making it available to its target users to ensure successful deployment and user satisfaction. During this phase, data will be collected for the dataset of the developed system.

Review Phase: Reviewing the finished iteration and gathering user feedback will constitute this final phase, which will determine the effectiveness of the system that was built. In addition to ensuring that the online application screening tool, Auticheck, satisfies the expectations of target users, the input obtained during this phase will help identify areas for improvement in the system's future revisions.

CHAPTER 4 RESULTS AND DISCUSSION

This chapter presents the results obtained from training and testing the Convolutional Neural Network (CNN) model, including its accuracy, sensitivity, and specificity. Additionally, the design of the web application's front-end is detailed, along with an overall evaluation of the system.

Implementation

Data Acquisition

The dataset was acquired from Kaggle (https://www.kaggle.com/datasets/fabdelja/autism-screening-for-toddlers). It consists of 1054 screening data points for toddlers using Q-CHAT 10. Figure 15 shows the screenshot of the dataset.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Case_No	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	Age_Mons	Qchat-10-	Sex	Ethnicity	Jaundice	Family_me	Who completed	Class/ASD Traits	
2	1	0	0	0	0	0	0	1	1	0	1	28	3	f	middle eastern	yes	no	family member	No	
3	2	1	1	0	0	0	1	1	0	0	0	36	4	m	White European	yes	no	family member	Yes	
4	3	1	0	0	0	0	0	1	1	0	1	36	4	m	middle eastern	yes	no	family member	Yes	
5	4	1	1	1	1	1	1	1	1	1	1	24	10	m	Hispanic	no	no	family member	Yes	
6	5	1	1	0	1	1	1	1	1	1	1	20	9	f	White European	no	yes	family member	Yes	
7	6	1	1	0	0	1	1	1	1	1	1	21	8	m	black	no	no	family member	Yes	
8	7	1	0	0	1	1	1	0	0	1	0	33	5	m	asian	yes	no	family member	Yes	
9	8	0	1	0	0	1	0	1	1	1	1	33	6	m	asian	yes	no	family member	Yes	
10	9	0	0	0	0	0	0	1	0	0	1	36	2	m	asian	no	no	family member	No	
11	10	1	1	1	0	1	1	0	1	1	1	22	8	m	south asian	no	no	Health Care Prof	Yes	
12	11	1	0	0	1	0	1	1	0	1	1	36	6	m	Hispanic	yes	yes	family member	Yes	
13	12	1	1	1	1	0	1	1	1	0	1	17	8	m	middle eastern	yes	no	family member	Yes	
14	13	0	0	0	0	0	0	0	0	0	0	25	0	f	middle eastern	yes	no	family member	No	
15	14	1	1	1	1	0	0	1	0	1	1	15	7	f	middle eastern	yes	no	family member	Yes	
16	15	0	0	0	0	0	0	0	0	0	0	18	0	m	middle eastern	no	no	family member	No	
17	16	1	1	1	0	1	0	1	1	0	1	12	7	m	black	no	no	family member	Yes	
18	17	0	0	0	0	0	0	0	0	0	0	36	0	m	middle eastern	no	yes	family member	No	
19	18	1	1	1	0	1	1	1	1	0	1	12	8	f	middle eastern	yes	no	family member	Yes	
20	19	1	0	0	0	1	0	0	0	0	1	29	3	f	middle eastern	no	no	family member	No	
21	20	1	1	1	0	1	0	1	1	0	1	12	7	f	black	no	no	family member	Yes	
22	21	1	0	0	1	1	1	1	1	1	0	36	7	m	middle eastern	no	no	family member	Yes	

Figure 15. Screenshot of the dataset

Training of the model

Python was the primary language used to build the CNN model using the libraries Tensorflow, Scikit-learn, and Keras. The development environment was a Jupyter notebook in Visual Studio Code.

The preprocessed dataset was split into a 70% training set and a 30% testing set. Subsequently, a grid search technique was conducted to determine the optimal values for the model's hyperparameters including the number of 1D CNN layers and filters, max pooling size, number of dense layers and related filters, dropout rate, and optimizer. As shown in Figure 16, based on the grid search, the CNN model with the best performance includes a relu activation, two 32-filter convolutional layers, two 64-filter dense layers with 30% dropout layer each, and two max pooling layers.

```python
best_params = grid_result.best_params_
for layer, params in best_params.items():
    print(layer + ": " + str(params))
```

```
activation: relu
conv_neurons: 32
dense_neurons: 64
dropout_rate: 0.3
num_conv_layers: 2
num_dense_layers: 2
pool_size: 2
```

Figure 16. Grid Search Results

Web Application Development

The researchers used Flask version 2.2.3 as the web application framework to develop the system. Javascript was used for the web application's interactivity and dynamic functionality. The researchers also utilized Tailwind CSS’s utility-first approach in styling, facilitating efficient and responsive design implementation.

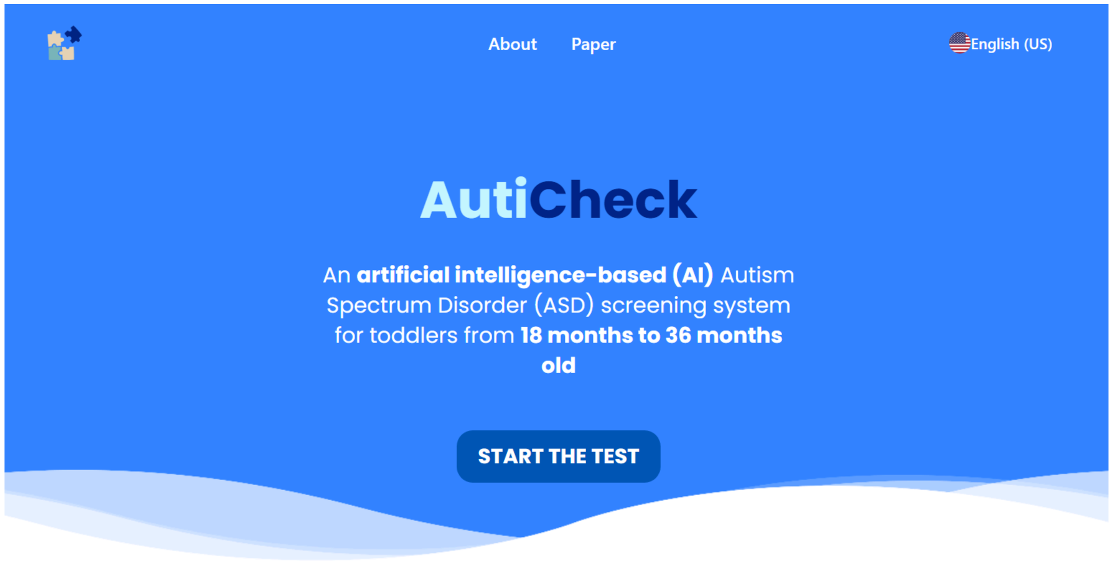

Figure 17. Landing Page of AutiCheck

Figure 17 shows the landing page of the web application, where a brief description of the screening system is stated and also indicates the age range of the toddlers subject to the screening test. To officially start the screening test, pressing the "Start the Test" button will navigate the user to the preliminary questions needed for the screening test.

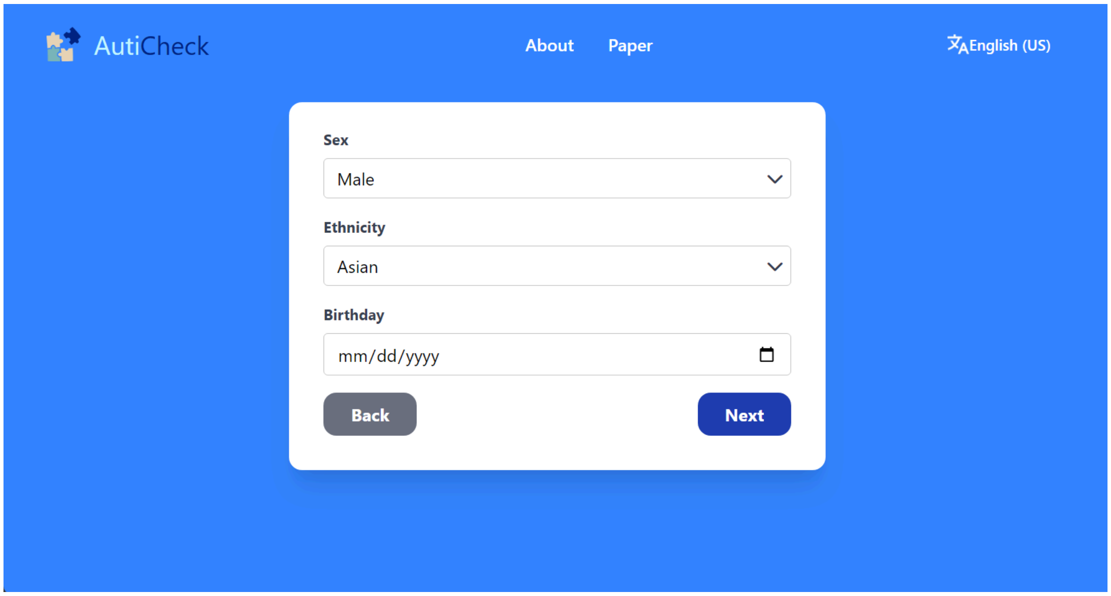

Figure 18. Preliminary Question 1 Page/Screen

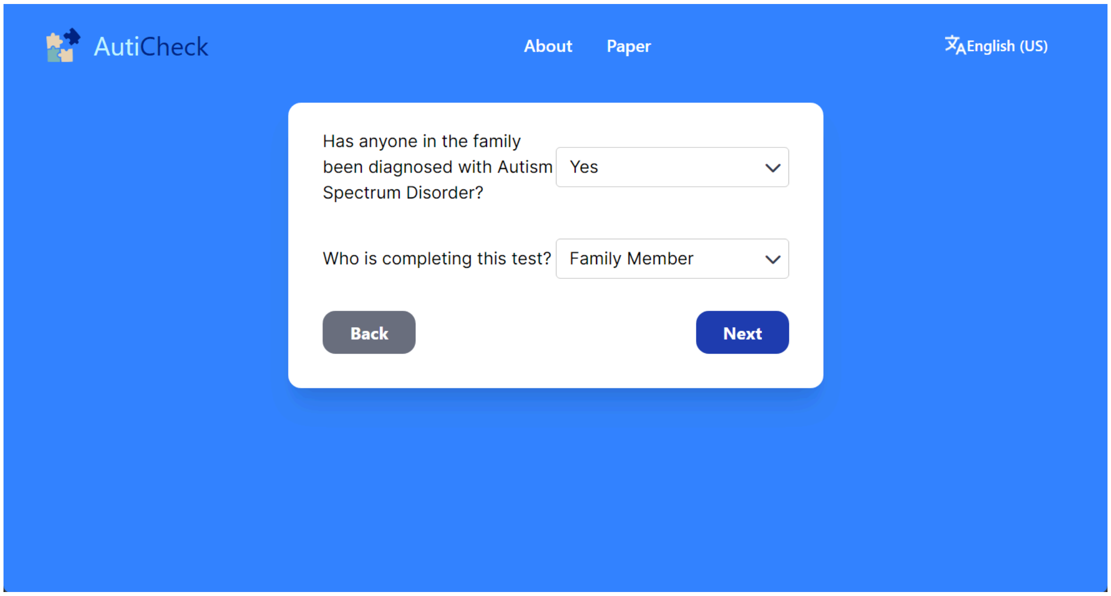

Figure 19. Preliminary Question 2 Page

Figure 18 and 19 shows the necessary preliminary questions to be asked by the system about. The preliminary part of the screening contains 4 questions; gender, date of birth, patient's family history of having ASD, and the person who will be answering the screening test. After which the preliminary questions were answered by the user, the system will navigate to the 1st official question of the screening.

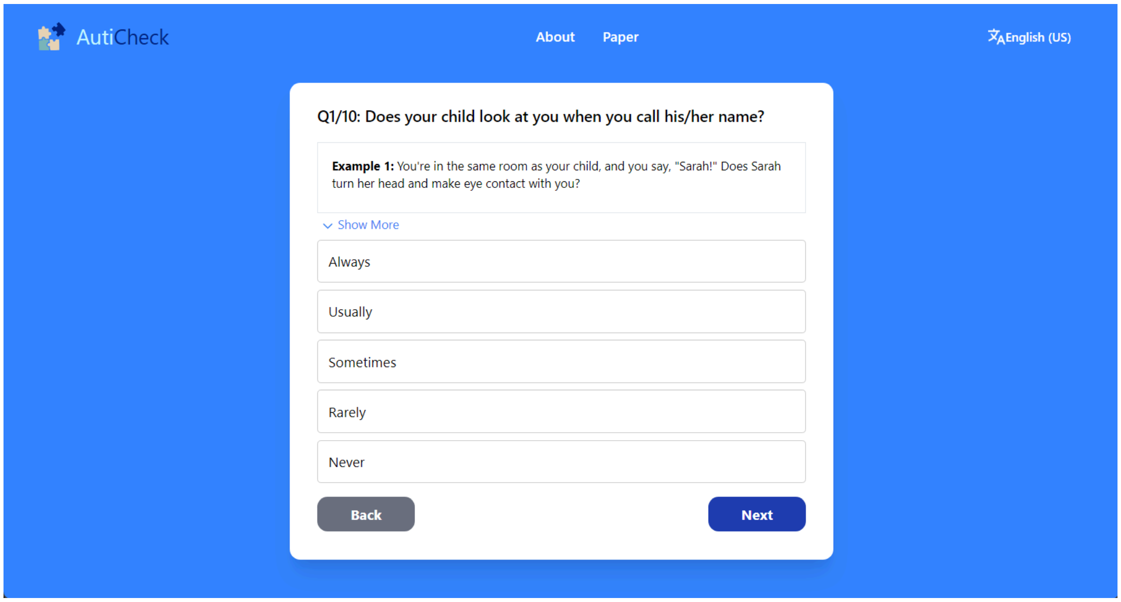

Figure 20. Q-Chat Screening Tool Question 1

Figure 20 shows the 1st question of Q-Chat screening tool to be asked by the web application. It will follow by another 9 questions with different choices depending on the question that is being asked.

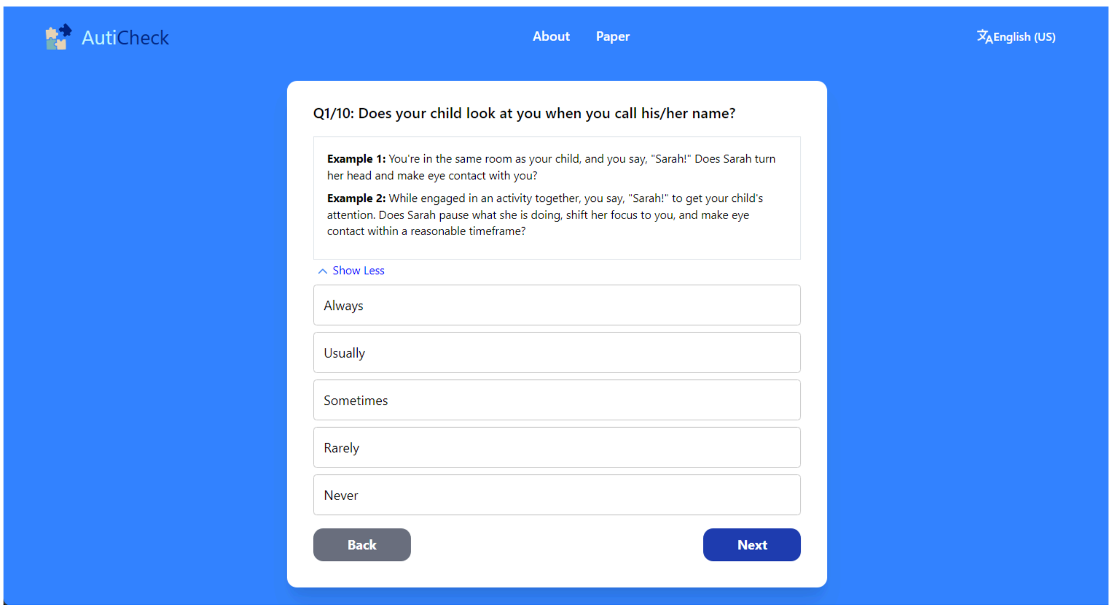

Figure 21. Q-Chat Screening Tool Question 1 with expanded examples

Figure 21 shows the dropdown feature of example scenarios that are provided for each question that will serve as a guide to users for understanding further each question.

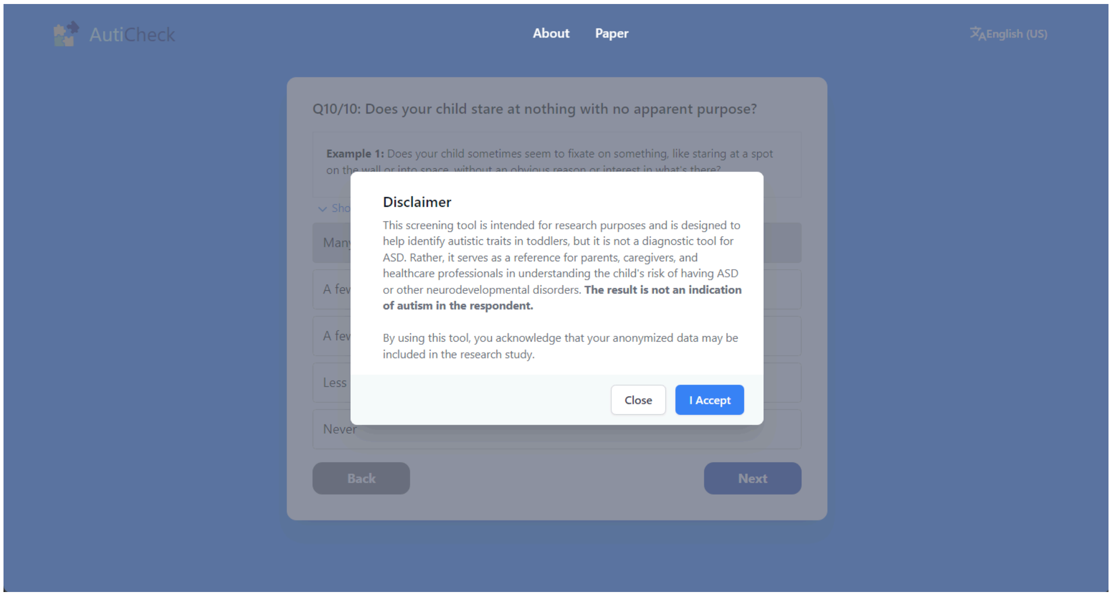

Figure 22. Disclaimer Popup Dialog

Figure 22 shows the disclaimer popup that will appear after the user has completed answering the 10 screening questions.

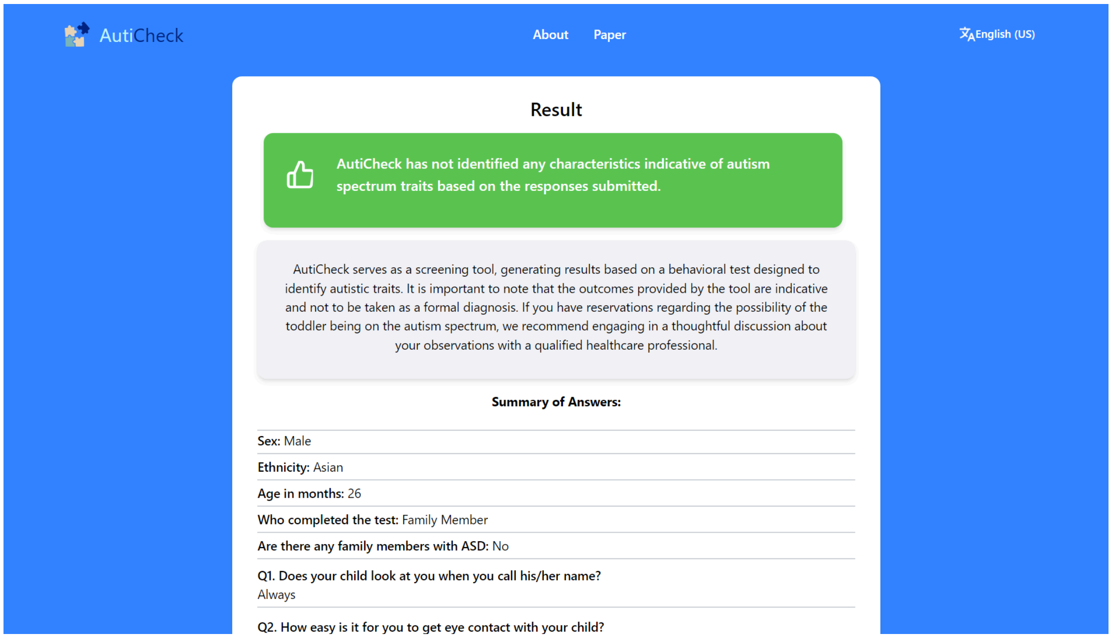

Figure 23. Generated Result Screen

The outcome of the web application system is displayed in Figure 23, which also recommends seeing a medical professional for a proper diagnosis. It indicates whether the toddler is at risk of developing an ASD or any other developmental issue. Then, a summary of the answers can be found below.

Results Interpretation and Analysis

CNN Model Performance

The accuracy is calculated as the percentage of correct classifications out of the total number of tests conducted. For this system, if the CNN likelihood prediction exceeds 50%, the system responds with "true" to indicate the presence of ASD traits in the subject. In contrast, if the likelihood prediction is below 50%, the system responds with "false" to indicate the low likelihood of ASD traits.

Sensitivity is a measure that is frequently used in binary classification, especially in medical testing and screening studies. It is also referred to as the "true positive rate." It measures the proportion of tests that are correctly classified as true positives. In the context of ASD risk detection, sensitivity represents the ratio of subjects with ASD risk correctly identified by the test. It provides insight into how effectively the test can detect individuals with ASD.

Specificity measures the percentage of tests that accurately identify people who do not have the ailment;

these people are referred to as true negatives. In other words, specificity measures the accuracy of the test in correctly classifying subjects without ASD.

Table 4. Performance of the CNN Model

Fold	Training Loss(binary_crossentropy)	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	0.0246	99.52	100	98.48
2	0.0397	99.05	98.63	100
3	0.0307	99.05	98.63	100
4	0.0466	99.05	99.31	98.56
5	0.0039	100	100	100

We validated the CNN prediction algorithm using the 5-fold cross-validation method. Table 4 shows a summary of the model's performance. We can see the training loss, mean accuracy, sensitivity, and specificity for each fold. Across the five folds of training, the mean training loss exhibited variation, ranging from 0.0039 to 0.0466. The model demonstrated consistently high performance in terms of accuracy, with values ranging from 99.05% to 100%. Sensitivity, remained robust across folds, ranging from 98.63% to 100%. Similarly, the specificity, maintained high levels, with values ranging from 98.4% to 100%. These results underscore the overall efficacy and reliability of the model across different training folds.

A confusion matrix, visualizing the classification report, is generated as depicted in Figure 24. In fold 2, the model performed well in classifying true negatives and true positives. However, there were some misclassifications for the false negatives as seen in the figure.

Overall, CNN achieved an impressive average testing accuracy of 99.33%. The mean sensitivity, measuring the ability to correctly identify positive cases, was 99.31%, while the mean specificity, indicating the accuracy in identifying negative cases, was 99.38%.

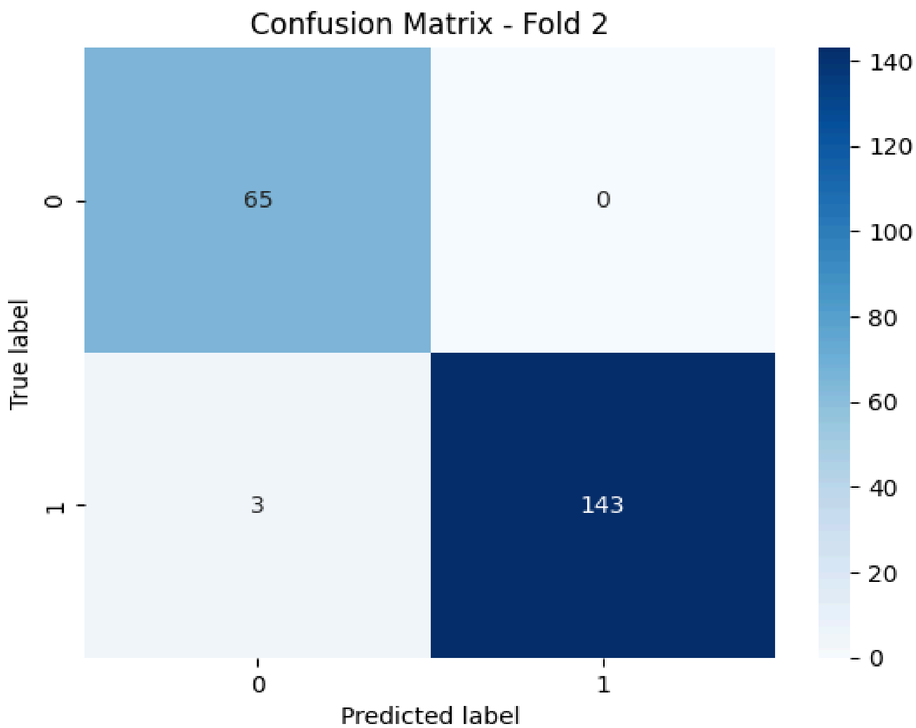

Figure 24. Confusion Matrix in Fold 2

Additionally, the training accuracies were comparable to the testing accuracies, as shown in Figure 25, indicating the absence of overfitting. This was also supported by the low amount of loss in both training and testing, as visualized. This can be attributed to the implementation of dropout regularization, which effectively constrained the memory capacity of the CNN and encouraged it to focus on learning the distinctive patterns associated with autism.

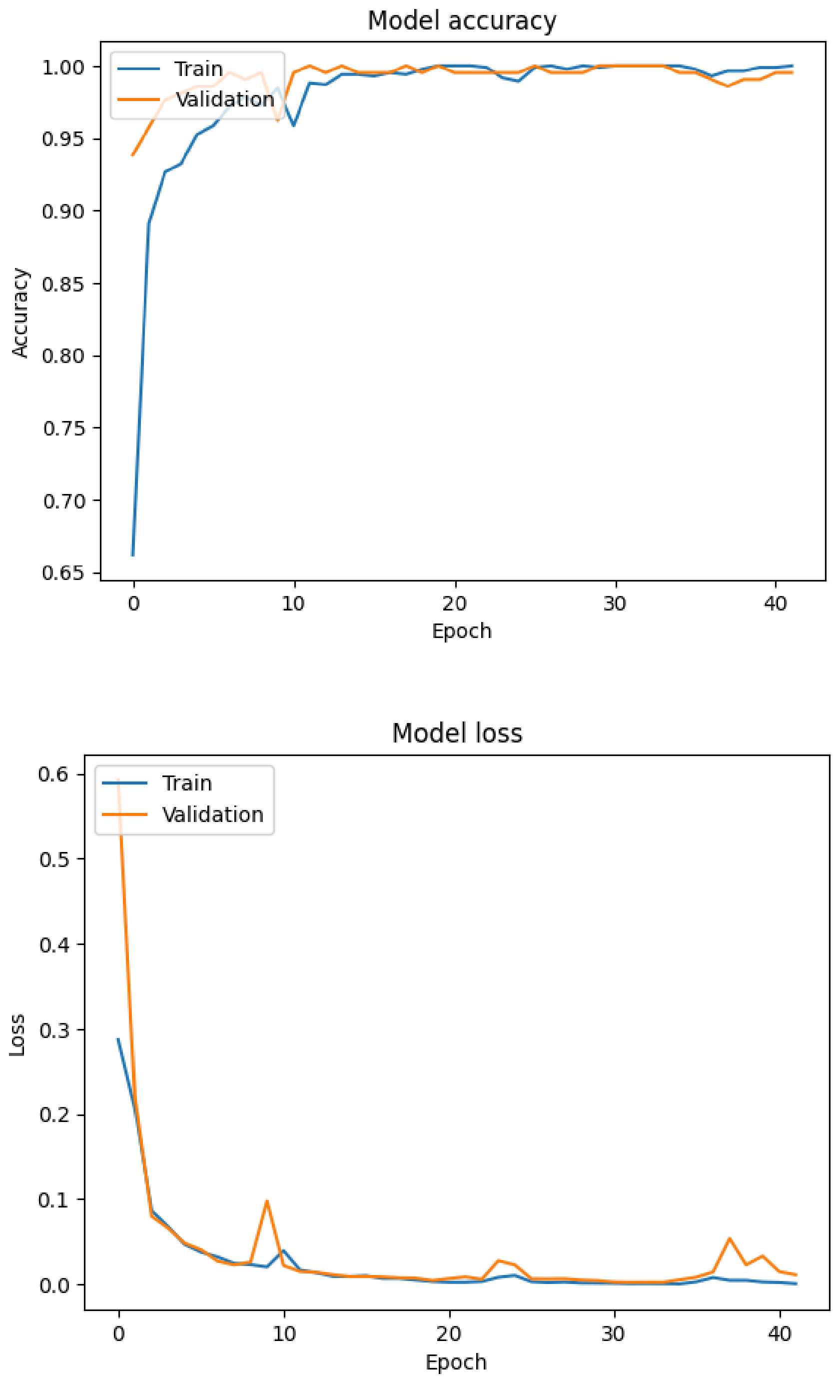

Figure 25. Training and validation history with 40 epochs

System Evaluation Results

The ISO/IEC 25010 standard evaluation framework was used to assess the system. Twelve people in total, including IT specialists, parents and guardians, medical professionals, and our consultant pediatrician participated in the system evaluation. The evaluation legend presented in Table 5 provides a reference for interpreting the mean scores assigned to software quality standards according to ISO/IEC 25010. The scale categorizes mean scores into five descriptive scales: Excellent, Good, Fair, Poor, and Very Poor. Each scale corresponds to a range of mean scores, facilitating a quick assessment of the overall quality of the software based on its mean evaluation score. All eight of the characteristics that the instrument evaluated—Functional Stability, Performance Efficiency, Compatibility, Usability, Security, Reliability, Maintainability, and Portability—were rated as "Excellent" overall, with a mean score of 4.407 as depicted in the overall summary found in Table 6. This indicates that the general usability of the system satisfies user needs.

Table 5. ISO/IEC 25010 Software Quality Standards Scale

Scales of Mean	Description
5 - 4.1	Excellent
4 - 3.1	Good
3 - 2.1	Fair
2 - 1.1	Poor
1	Very Poor

Table 6. Overall Summary of ISO/IEC 25010 Software Quality Standards Evaluation Result

Characteristics	Mean	Description
Functional Stability	4.305555556	Excellent
Performace Efficiency	4.638888889	Excellent
Compatibility	4.291666667	Excellent
Usability	4.513888889	Excellent
Reliability	4.416666667	Excellent
Security	4.283333333	Excellent
Maintainability	4.416666667	Excellent
Portability	4.393939394	Excellent
OVERALL	**4.407575758**	**Excellent**

Moreover, the evaluation results presented in Table 7 offer a more valuable insights into the perceived quality of the software, as assessed by different groups of evaluators: IT Professionals, Medical Experts, and Parents/Guardians.

From the perspective of IT Professionals, the software generally received high ratings across most characteristics, with particularly strong ratings for

Performance Efficiency, Usability, and Reliability. This suggests that IT Professionals perceive the software as being efficient, user-friendly, and dependable, which are essential attributes for software systems in various domains. However, there are slightly lower ratings for Functional Stability and Portability, indicating potential areas for improvement in terms of the software's robustness and adaptability.

In contrast, Medical Experts rated the software slightly lower across most characteristics compared to IT Professionals. Notably, Medical Experts gave lower ratings for Functional Stability and Security. This discrepancy could be attributed to Medical Experts' specific requirements and expectations regarding software stability and security in the context of healthcare applications. Nonetheless, the software still received commendable ratings for Performance Efficiency and Usability, indicating its potential usefulness in medical settings.

Parents/Guardians, on the other hand, provided the highest ratings overall for the software. They rated the software highest in terms of Functional Stability, Usability, and Portability. These ratings suggest that Parents/Guardians perceive the software as reliable, easy to use, and accessible across different devices, which are crucial factors for ensuring a positive user experience, especially for individuals with varying levels of technical expertise.

The discrepancies in ratings across different characteristics underscore the need for targeted improvements in specific areas to enhance the overall quality and usability of the software. By addressing the concerns raised by different evaluators, developers can iteratively refine the software to better meet the diverse needs of its users and stakeholders. Further information on the ISO/IEC 25010 result can be found on Appendix P.

Table 7. ISO/IEC 25010 Software Quality Standards Evaluation Result Per Group

Characteristics	**IT Professionals (Mean)**	**Medical Experts (Mean)**	**Parents/ Guardians (Mean)**
Functional Stability	4.533333333	3.5	4.75
Performace Efficiency	4.8	4.5	4.66666666
Compatibility	4.2	4	4.625
Usability	4.666666667	4.0833333	4.70833333
Reliability	4.3	4.4375	4.5
Security	3.8	4.15	4.8
Maintainability	4.32	4.1	4.6
Portability	4.266666667	4.3333333	4.5
OVERALL	**4.360833333**	**4.1380208**	**4.13802082**

CHAPTER 5 SUMMARY, CONCLUSIONS, RECOMMENDATIONS

Summary of the Proposed Study and Implementation

While timely diagnosis of ASD is crucial for the overall well-being of individuals, the formal diagnostic process is often prolonged due to the demands of training, administration, scoring, and consensus coding. Conventional screening tools for toddlers, such as MCHAT and QCHAT, are commonly employed. However, the efficacy of their classification outcomes is heavily reliant on factors such as the method's items, the expertise of the user conducting the screening, and the manually crafted rules governing the scoring function within these tools. The study aimed to design and integrate deep learning, specifically the CNN algorithm, into the Q-CHAT 10 ASD screening tool for toddlers.

The researchers trained the CNN model using a dataset from Kaggle, comprising 1054 toddler screening data points based on Q-CHAT 10. After preprocessing the dataset, it was supplied to the model alongside optimal hyperparameters determined through grid search. Python was the main programming language, with development conducted in Jupyter Notebook within Visual Studio Code

The final model was integrated into the web application via Flask, with JavaScript handling the dynamic aspects and Tailwind CSS employed for styling and layout.

Parents, caregivers, or healthcare professionals can conveniently respond to the QCHAT-10 questionnaire through our web application. Upon completion, the model generates a comprehensive summary of the user's responses, indicating the likelihood of ASD in the toddler.

Summary of Findings

The Convolutional Neural Network (CNN) demonstrated a remarkable average testing accuracy of 99.33%. The average sensitivity, representing the capability to accurately detect positive cases, stood at 99.31%, while the average specificity, reflecting the precision in recognizing negative cases, reached 99.38%. The system was also assessed using the ISO/IEC 25010 standard evaluation framework, and all eight characteristics were rated as "Excellent," indicating a high degree of quality and effectiveness in meeting user needs.

Conclusions

The integration of deep learning, specifically the Convolutional Neural Network (CNN) algorithm, into the Q-CHAT 10 ASD screening tool for toddlers has proven to be highly effective. By taking advantage of CNN's capability of extracting intricate patterns and features from complex data, the system achieves exceptional levels of accuracy, sensitivity, and specificity in identifying potential cases of ASD. These results suggest that the it has the potential to improve the efficiency of ASD screening processes, ultimately leading to more timely diagnoses.

Furthermore, the system's evaluation against the ISO/IEC 25010 standard, which assesses various software quality characteristics, reveals consistently high ratings across all dimensions. This demonstrates the system's effectiveness in meeting the diverse needs of users, including parents, caregivers, and healthcare professionals.

Overall, this approach represents a promising advancement in ASD screening. By providing a reliable and user-friendly tool for identifying potential cases of ASD in toddlers, the system has the potential to positively impact the lives of individuals and families affected by autism spectrum disorder.

Recommendations

For future studies, the researchers like to explore other machine learning techniques such as logistic regression and decision trees, as well as various deep learning algorithms and rule-based learning algorithms. Furthermore, the researchers would also wish to explore the use of the CNN algorithm with datasets that contain answers from other screening tools and datasets with more complex features such as images and videos. Due to ethical considerations, data gathering and acquisition would be a challenge for future studies involving using deep learning to enhance ASD screening. If such datasets become available in the future, this would greatly aid in advancing research and studies about ASD screening. This will help individuals diagnose their condition early and get help from medical experts.

Furthermore, feedback from our domain expert and testers during the ISO evaluation process yields further valuable insights for system enhancement. Strengthening security measures and enforcing stringent confidentiality protocols for the database emerges as a critical priority to safeguard sensitive information of the users. Moreover, refining the user interface design, with a specific focus on improving accessibility features, can greatly enhance the usability and inclusivity of the system. Exploring and implementing color schemes that are conducive to individuals with ASD can also contribute to a more user-friendly and accommodating interface.

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Appendices

Appendix A - Letter to the Adviser

Dr. Frank Elijorde

Attachment 3

	INVITATION LETTER FOR ADVISER	Document No.	**WVSU-ICT-SOI-03-F03**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 1 of 1**

December 9, 2022

Dr. Frank I. Elijorde
Associate Dean (Full-time Professor)
College of ICT – WVSU Main
General Luna St, La Paz, Iloilo City, 5000 Iloilo

Dear **Dr. Elijorde,**

The undersigned are BS in Computer Science Research 1/Thesis 1 students of CICT, this university. Our thesis/capstone project title is ***"Machine Learning Algorithm for Classification of Autism Spectrum Disorder."***

Knowing of your expertise in research and on the subject matter, we would like to request you to be our **ADVISER**.

We are positively hoping for your acceptance. Kindly check the corresponding box and affix your signature in the space provided. Thank you very much.

Respectfully yours,

1. Bagsit, Eunice D.
2. Gison, Maria Joeanne A.
3. Quintilla, Mayenel O.
4. Sondia, Kenji John B.
5. Tenan, Kim Jasper T.

PS:

Adviser are tasked to work with the students in providing direction and assistance as needed in their thesis/capstone project. They shall meet with the students weekly or as needed to provide direction, check on progress and assist in resolving problems until such a time that the students passed their defenses and submit their final requirements, as well as, preparing their evaluations and grades.

Action Taken:

❍ I Accept.

❍ Sorry. I don't accept.

Signature over printed name of the Adviser

CC:

CICT Dean
Research Coordinator
Group
**To be accomplished in 4 copies*

Dr. Arnel Secondes

Attachment 3

	INVITATION LETTER FOR ADVISER	Document No.	**WVSU-ICT-SOI-03-F03**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 1 of 1**

December 9, 2022

Dr. Arnel N. Secondes
Full-time Professor
College of ICT – WVSU Main
General Luna St, La Paz, Iloilo City, 5000 Iloilo

Dear **Dr. Secondes,**

The undersigned are BS in Computer Science Research 1/Thesis 1 students of CICT, this university. Our thesis/capstone project title is ***"Machine Learning Algorithm for Classification of Autism Spectrum Disorder."***

Knowing of your expertise in research and on the subject matter, we would like to request you to be our **ADVISER**.

We are positively hoping for your acceptance. Kindly check the corresponding box and affix your signature in the space provided. Thank you very much.

Respectfully yours,

1. Bagsit, Eunice D.
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4. Sondia, Kenji John B.
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PS:

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Action Taken:	
❍ I Accept.	
❍ Sorry. I don't accept.	Signature over printed name of the Adviser

CC:

CICT Dean
Research Coordinator
Group
**To be accomplished in 4 copies*

Appendix B - Consultation Letter to Developmental Pediatrician

West Visayas State University
COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
Luna St., La Paz, Iloilo City 5000
Iloilo, Philippines
* Trunkline: (063) (033) 320-0870 loc 1403 * Telefax No.: (033) 320-0879
* Website: www.wvsu.edu.ph * Email Address: cict@wvsu.edu.ph

April 3, 2023

DR. CELINA CORDERO-GELLADA
VP for Medical and Allied Sciences
West Visayas State University

Dear Ma'am,

The undersigned are BS Computer Science students of the College of ICT at West Visayas State University. As part of our thesis work, we are currently conducting a research entitled "Auticheck: An ASD Classification System Using Convolutional Neural Network."

In relation to that, we would like to have a consultation with you about our research and ask for your insights as a domain expert. We are hoping for your positive response to this request. Thank you very much.

Respectfully yours,

Eunice D. Bagsit | Maria Joeanne A. Gison | Mayenel O. Quintilla

Kenji John B. Sondia | Kim Jasper T. Tenan

Noted:

____
Dr. Frank I. Elijorde
Thesis Adviser

____
Dr. Ma. Beth S. Concepcion
Dean, CICT

Appendix C - Consultation Log

Attachment 4

	THESIS/CAPSTONE PROJECT CONSULTATION LOG FORM	Document No.	**WVSU-ICT-SOI-03-F04**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**ICT OFFICE**
		Page No.	**Page 1 of 5**

Academic Year 2022-2023

Title: Auticheck: An ASD Screening Tool For Toddlers Using Convolutional Neural Networks	
Group Members:	
1. Eunice D. Bagsit	4. Kenji John B. Sondia
2. Maria Joeanne A. Gison	5. Kim Jasper T. Tenan
3. Mayenel O. Quintilla	

Date	Attendance	Comments/Suggestions/Instructions	Signature
Feb. 23, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Start with methodology before consulting to a domain expert (COM) • Choose an algorithm • Establish concept & methodology (RRL with dataset) • Google Drive Repository access • Official letter when engaging outside school • Consultation form Literature mapping – RRL divided into sub topics (at least 15 references)	
Mar. 06, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Gison • Quintilla • Sondia • Tenan	• Specific objectives, must be measurable • Objectives pertaining to evaluation • Adapt evaluation methods of related literature • Rephrase objectives that includes adults & other subjects • After 20% presentation, work or contact with domain expert • Dataset in kaggle – secure the questions that correspond with the dataset • Designate tasks • Edit related literature on closing part with 2-3 sentences that relate to the	

	Attachment 4 THESIS/CAPSTONE PROJECT CONSULTATION LOG FORM	Document No.	**WVSU-ICT-SOI-03-F04**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**ICT OFFICE**
		Page No.	**Page 2 of 5**

		study and contribution of own study over existing study/system • Theoretical diagram	
Apr. 03, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Prepare a copy of concept paper, letter of intention and related questions for the domain expert (COM) • Present the dataset to the domain expert • Find any localize dataset • Prototype (Jupyter notebook, references from github and codes)	
Apr. 12, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Prototype demonstrating the data (either code/dataset validated by domain expert) • Justification letter (to be vouched by sir frank) • Edit and modify manuscript	
Apr. 17, 2023	Consultant: Dr. Celina Cordero-Gellada Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• ADOS – common screening tool • M-CHAT – 36 months , 20-23 items • Screening ≠ Diagnosis • Must not over/under diagnose • Must be culturally relevant to the Philippines • Preferably screening at earliest age (Toddler) • Need to identify the gender of the toddler • Follow-up form • Philippine context- culture, capture target audience	*Refer to transcript letter for signature*

	Attachment 4 THESIS/CAPSTONE PROJECT CONSULTATION LOG FORM	Document No.	**WVSU-ICT-SOI-03-F04**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**ICT OFFICE**
		Page No.	**Page 3 of 5**

Apr. 18, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Gison • Quintilla • Sondia • Tenan	• Try to contact original author of M-Chat questionnaire • Pursue with Q-Chat (Toddler questionnaire) if there is still no response from original author • Recommend M-Chat for future researchers of the study • Finalization of subject age coverage – Toddler Representation schedule	
May 8, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Checked manuscript • Deduct, split dataset • Storyboarding (ux flow) • Emphasize progress with the de • Assure and coordinate with de the progress of the chosen screening tool • Emphasize age group of toddlers	
May 29, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Improve SDLC • Rephrase and finalize objectives • Incorporate literature mapping method in improving theoretical framework • Continue coordinating with DE with the added feature of the web application • Consult with a language expert with the translations of example scenarios • Revise and be specific with the system architecture	

Attachment 4

	THESIS/CAPSTONE PROJECT CONSULTATION LOG FORM	Document No.	**WVSU-ICT-SOI-03-F04**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**ICT OFFICE**
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May 29, 2023	Consultant: Dr. Celina Cordero-Gellada Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Basis of questionnaire • Emphasize that it's not a diagnostic tool • Be specific about the toddler age • Get date of birth • Put sample scenarios that will help refer to the questions	*Refer to transcript letter for signature*
Sept .29, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Bagsit • Gison • Quintilla • Sondia • Tenan	• Manuscript for turnitin • Reduce similarity index • Manuscript revisions	
Dec 19, 2023	Consultant: Dr. Frank I. Elijorde Consultees: • Gison • Quintilla • Sondia	• Reduce to 20% or less in Turnitin index • Chapter 4 & 5 contents • Upload bare format of the paper • Questionnaire translation • Usability testing • ISO questionnaire and respondents • System evaluation	
Feb. 7, 2024	Consultant: Dr. Frank I. Elijorde Consultees: • Gison • Quintilla • Sondia	• Language teacher (for translation) – Language Department • Letter – Validation of Transcription • Provide transcript of consultation – Doc Gellada • Modification of questionnaire • Transcript of interviews and consultaions	

	Attachment 4 THESIS/CAPSTONE PROJECT CONSULTATION LOG FORM	Document No.	WVSU-ICT-SOI-03-F04
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**ICT OFFICE**
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		• Ask for general thoughts of the study, recommendations, and insights from domain expert • If possible ask for a picture (Proof of engagement with Domain expert) • Questionnaire – ISO standard • Respondents (5-10 from different stakeholders: IT expert, medical practioners, and parents or guardians)	
Mar 13, 2024	Consultant: Dr. Celina Cordero-Gellada Consultees: • Bagsit • Quintilla • Sondia	• Disclaimer should follow after the title page • Emphasized Screening tool • Recommended result to be emailed to parents/respondents. • Error protection system, previous answers cannot be recovered	*Refer to transcript letter for signature*

Adviser: DR. FRANK I. ELIJORDE

Consultation Schedule: M - 10:00 - 11:30A.M. , W - 10:00AM - 11:30A.M

Appendix D - Final Defense Adviser's Recommendation Letter

Attachment 7

	ADVISER'S RECOMMENDATIONS	Document No.	WVSU-ICT-SOI-03-F07
		Issue No.	1
		Revision No.	0
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 1 of 1**

(For Thesis Defense)

☐ 20% ☐ 50% ☑ Final Defense

This is to certify that the thesis entitled:

AUTICHECK: AN ASD SCREENING TOOL FOR TODDLERS USING CONVOLUTIONAL NEURAL NETWORKS

has been presented to me by the proponents whose names indicated below, and has been preliminarily evaluated and is ready for the Defense Evaluation.

Now therefore, I hereby **RECOMMEND/ENDORSE** the said thesis group (with their thesis document and system) for evaluation by the panel of Jurors for THESIS DEFENSE as scheduled.

DR. FRANK I. ELIJORDE
Adviser's Name & Signature

DR. ARNEL N. SECONDES
Name of Co-Adviser (if there is any)

Date: DECEMBER 20, 2023

Group Members:

1. Eunice D. Bagsit
2. Maria Joeanne A. Gison
3. Mayenel O. Quintilla
4. Kenji John B. Sondia
5. Kim Jasper T. Tenan

Note: *This form should be placed on top of the thesis document that will be submitted for the defense. No group will be entertained in the defense without this document.*

Appendix E - Letter of Request to the Adviser for Endorsement

Appendix F - Letter of Request to the Technical Editor

	ADVISER'S ENDORSEMENT FORM (For Thesis Manuscript)	Document No.	**WVSU-ICT-SOI-03-F10**
		Issue No.	**1**
		Revision No.	**0**
	WEST VISAYAS STATE UNIVERSITY	Date of Effectivity:	**April 27, 2018**
		Issued by:	**CICT**
		Page No.	**Page 1 of 1**

Respectfully endorsed to the **Technical Editor**, the attached manuscript of the thesis entitled:

"AUTICHECK: AN ASD SCREENING TOOL FOR TODDLERS USING CONVOLUTIONAL NEURAL NETWORKS"

Said manuscript has been presented to me for preliminary evaluation and guidance, and after a series of corrections/directions given which was implemented by the proponents whose names are listed hereunder and their thorough research, we have come to its completion.

Now therefore, I hereby **ENDORSE** the said thesis manuscript to the Technical Editor for **TECHNICAL EDITING**.

DR. FRANK I. ELIJORDE
Adviser's Name & Signature

Date: MAY 06, 2024

Group Members:
1. EUNICE D. BAGSIT
2. MARIA JOEANNE A. GISON
3. MAYENEL O. QUINTILLA
4. KENJI JOHN B. SONDIA
5. KIM JASPER T. TENAN

Note: *This form should be accomplished and signed if the corrections and changes made by the adviser have been implemented and a new copy of the document have been printed for checking and submission to the next editor*

Appendix G - Letter of Request to the English Editor

Appendix H - Letter of Request to the Thesis Format

Appendix I - Letter of Request to the Thesis Coordinator/Certification for Bookbinding

Appendix J - Signed Letter for Output and Final Build Evaluation

Appendix K - Dataset Screenshots

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Case_No	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	Age_Mons	Sex	Ethnicity	Family_me	Class/ASD
1	0	0	0	0	0	0	1	1	0	1	28	f	middle eastern	no	No
2	1	1	0	0	0	1	1	0	0	0	36	m	White European	no	Yes
3	1	0	0	0	0	0	1	1	0	1	36	m	middle eastern	no	Yes
4	1	1	1	1	1	1	1	1	1	1	24	m	Hispanic	no	Yes
5	1	1	0	1	1	1	1	1	1	1	20	f	White European	yes	Yes
6	1	1	0	0	1	1	1	1	1	1	21	m	black	no	Yes
7	1	0	0	1	1	1	0	0	1	0	33	m	asian	no	Yes
8	0	1	0	0	1	0	1	1	1	1	33	m	asian	no	Yes
9	0	0	0	0	0	0	1	0	0	1	36	m	asian	no	No
10	1	1	1	0	1	1	0	1	1	1	22	m	south asian	no	Yes
11	1	0	0	1	0	1	1	0	1	1	36	m	Hispanic	yes	Yes
12	1	1	1	1	0	1	1	1	0	1	17	m	middle eastern	no	Yes
13	0	0	0	0	0	0	0	0	0	0	25	f	middle eastern	no	No
14	1	1	1	1	0	0	1	0	1	1	15	f	middle eastern	no	Yes
15	0	0	0	0	0	0	0	0	0	0	18	m	middle eastern	no	No
16	1	1	1	0	1	0	1	1	0	1	12	m	black	no	Yes
17	0	0	0	0	0	0	0	0	0	0	36	m	middle eastern	yes	No
18	1	1	1	0	1	1	1	1	0	1	12	f	middle eastern	no	Yes
19	1	0	0	0	1	0	0	0	0	1	29	f	middle eastern	no	No
32	0	0	0	0	0	0	0	0	0	0	12	f	middle eastern	no	No
33	0	0	0	0	0	0	0	0	0	1	15	f	middle eastern	no	No
34	0	0	0	0	0	0	0	0	0	0	12	f	middle eastern	no	No
35	0	0	0	0	0	0	0	0	0	1	12	f	middle eastern	no	No
36	1	1	1	1	1	1	1	1	1	1	15	f	middle eastern	no	Yes
37	0	0	0	0	0	0	0	0	0	1	15	f	middle eastern	no	No
38	0	0	0	0	0	0	0	0	0	0	15	f	middle eastern	no	No
39	0	0	0	0	0	0	0	0	0	0	15	f	middle eastern	no	No
40	0	0	0	0	0	0	0	0	0	1	15	f	middle eastern	no	No
41	0	0	0	0	0	0	0	0	0	1	12	f	middle eastern	no	No
42	0	0	0	0	0	0	0	0	0	0	15	f	black	no	No
43	0	0	0	0	0	0	0	0	0	0	15	f	black	no	No
44	0	0	0	0	0	0	0	0	0	0	15	f	middle eastern	no	No
45	0	0	0	0	0	0	0	0	0	1	15	f	middle eastern	no	No
46	0	0	0	0	0	0	1	0	0	1	19	m	asian	no	No
47	0	0	0	0	0	0	0	0	0	1	18	m	middle eastern	no	No
48	0	0	0	0	0	0	0	0	0	1	12	f	White European	no	No
49	0	0	0	0	0	0	0	0	0	1	14	f	White European	no	No
50	0	0	0	0	0	0	0	0	0	1	14	f	middle eastern	no	No
51	0	0	0	0	0	0	0	0	0	1	12	m	middle eastern	no	No

Appendix L - Sample Codes For Model Training

DATA PREPROCESSING STAGE

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from keras.utils import np_utils

# Split data into training and testing sets
X = asd.drop(['Class/ASD Traits'], axis=1)
y = asd['Class/ASD Traits']

# Perform one-hot encoding on categorical variables
categorical_vars = ['Sex', 'Ethnicity', 'Family_mem_with_ASD']
X_encoded = pd.get_dummies(X, columns=categorical_vars)
# Bin user age into categories of size three
age_bins = np.arange(12, 42, 3)
age_labels = np.arange(12, 39, 3)

X_encoded['Age_binned'] = pd.cut(X['Age_Mons'], bins=age_bins, labels=age_labels)
# Concatenate numerical and encoded categorical features
numerical_vars = ['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9', 'A10']
X_encoded = pd.concat([X_encoded[numerical_vars], X_encoded.drop(numerical_vars, axis=1)], axis=1)
```

```
# Build the CNN model
from keras.models import Sequential
from keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout# Define the model architecture
def build_model():
    model = Sequential()
    model.add(Conv1D(32, 3, activation='relu', input_shape=(X_encoded.shape[1], 1)))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Conv1D(32, 3, activation='relu'))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Flatten())
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(1, activation='sigmoid'))

    # Compile the model
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

    return model
```

+ Code + Markdo

```
# Build and compile the model
model = build_model()  # replace with your model architecture
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
```

Appendix M - Sample Code For Web Application Development

```python
new_data = pd.DataFrame(columns=['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7',
                                 'A8', 'A9', 'A10', 'Age_Mons','Sex', 'Ethnicity',
                                 'Family_mem_with_ASD'])

@app.route('/')
def index():
    return render_template('index.html')


@app.route('/preliminary1', methods=['GET', 'POST'])
def preliminary1():
    if request.method == 'POST':
        # Get form inputs
        sex = request.form['gender']
        ethnicity = request.form['ethnicity']
        birthday = datetime.strptime(request.form.get('birthday'), '%Y-%m-%d').date()
        present_date = datetime.now()
        age_in_months = (present_date.year - birthday.year) * 12 + (present_date.month - birthday.month)

        print("Age in months:", age_in_months)  # Debug print

        # Populate new_data DataFrame
        new_data.loc[0] = [None] * len(new_data.columns)
        new_data.loc[0, ['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9', 'A10', 'Age_Mons', 'Sex', 'Ethnicity', 'Family_mem_with_ASD']] =

        # Print the new_data before preprocessing
        print("New Data (before preprocessing):")
        print(new_data)

        return render_template('preliminary2.html', new_data=new_data)

    print("Rendering preliminary1.html")  # Debug print
    return render_template('preliminary1.html')
```

```python
@app.route('/q1', methods=['GET', 'POST'])
def q1():
    if request.method == 'POST':
        A1 = request.form.get('answer1')

        if not A1:
            error_message = "Please select an answer for Question 1."
            return render_template('q1.html', new_data=new_data, error_message=error_message)

        new_data.loc[0, 'A1'] = int(A1)

        return render_template('q2.html', new_data=new_data)

    print("Rendering q1.html")  # Debug print
    return render_template('q1.html')

# Add routes and functions for the remaining questions (question2, question3, ..., question10)

@app.route('/q2', methods=['GET', 'POST'])
def q2():
    if request.method == 'POST':
        A2 = request.form.get('answer2')

        if not A2:
            error_message = "Please select an answer for Question 2."
            return render_template('q2.html', new_data=new_data, error_message=error_message)

        new_data.loc[0, 'A2'] = int(A2)

        return render_template('q3.html', new_data=new_data)

    print("Rendering q2.html")  # Debug print
    return render_template('q2.html')

@app.route('/q3', methods=['GET', 'POST'])
```

Appendix N- ISO/IEC 25010 Evaluation Questionnaire

AutiCheck Usability Evaluation

Greetings! We are BS Computer Science students from West Visayas State University – College of Information and Communications Technology, currently conducting our research entitled, ***"AutiCheck: An ASD Screening Tool for Toddlers Using Convolutional Neural Networks."***

In this study, we developed a web application that can determine the likelihood of a autism in toddlers. It's essential to note that this tool doesn't serve as a diagnostic instrument; instead, it aims to pinpoint potential indicators or detect early signs associated with autism. The goal is to assist parents, guardians, or healthcare professionals in recognizing red flags and facilitating early intervention.

In line with this, we are inviting you to take part in our research by evaluating our web application through this questionnaire.

Instructions:

Kindly evaluate the degree to which our app has complied to the ISO/IEC 25010:2011 Software Product Quality criteria by checking the column from **1** being "**Poor**" to **5** being "**Excellent**".

Data Privacy: *In compliance with RA 10173 or the Data Privacy Act of 2012, the personal information provided by the respondents shall remain confidential and will only be used for the purpose or this research.*

kenjijohn.sondia@wvsu.edu.ph Switch account

* Indicates required question

Email *

Your email

Name:

Your answer

Field: *

- ○ Information Technology
- ○ Medicine/Health Care
- ○ Parent/Guardian

Next | Page 1 of 9 | Clear form

Functional Suitability

The degree to which a product or system provides functions that meet stated and implied needs when used under specified conditions.

Functional completeness - Degree to which the set of functions covers all the specified tasks and user objectives *

1 2 3 4 5

○ ○ ○ ○ ○

Functional correctness - Degree to which a product or system provides the correct results with the needed degree of precision. *

1 2 3 4 5

○ ○ ○ ○ ○

Functional appropriateness - Degree to which the functions facilitate the accomplishment of specified tasks and objectives. *

1 2 3 4 5

○ ○ ○ ○ ○

Performance Efficiency

The performance relative to the amount of resources used under stated conditions.

Time behavior - Degree to which the response and processing times and throughput rates of a product or system, when performing its functions, meet requirements. *

1	2	3	4	5
○	○	○	○	○

Resource utilization - Degree to which the amounts and types of resources used by a product or system, when performing its functions, meet requirements. *

1	2	3	4	5
○	○	○	○	○

Capacity - Degree to which the maximum limits of a product or system parameter meet requirements. *

1	2	3	4	5
○	○	○	○	○

Compatibility

Degree to which a product, system or component can exchange information with other products, systems or components, and/or perform its required functions while sharing the same hardware or software environment.

Co-existence - Degree to which a product can perform its required functions efficiently while sharing a common environment and resources with other products, without detrimental impact on any other product. *

1	2	3	4	5
○	○	○	○	○

Interoperability - Degree to which two or more systems, products or components can exchange information and use the information that has been exchanged. *

1	2	3	4	5
○	○	○	○	○

Usability

Degree to which a product or system can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use.

Appropriateness recognizability - Degree to which users can recognize whether a product or system is appropriate for their needs. *

1	2	3	4	5
○	○	○	○	○

Learnability - Degree to which a product or system can be used by specified users to achieve specified goals of learning to use the product or system with effectiveness, efficiency, freedom from risk and satisfaction in a specified context of use. *

1	2	3	4	5
○	○	○	○	○

Operability - Degree to which a product or system has attributes that make it easy to operate and control. *

1	2	3	4	5
○	○	○	○	○

User error protection. Degree to which a system protects users against making errors. *

1	2	3	4	5
○	○	○	○	○

User interface aesthetics - Degree to which a user interface enables pleasing and satisfying interaction for the user. *

1	2	3	4	5
○	○	○	○	○

Accessibility - Degree to which a product or system can be used by people with the widest range of characteristics and capabilities to achieve a specified goal in a specified context of use. *

1	2	3	4	5
○	○	○	○	○

Reliability

Degree to which a system, product or component performs specified functions under specified conditions for a specified period of time.

Maturity - Degree to which a system, product or component meets needs for reliability under normal operation. *

1	2	3	4	5
○	○	○	○	○

Availability - Degree to which a system, product or component is operational and accessible when required for use.

1	2	3	4	5
○	○	○	○	○

Fault tolerance - Degree to which a system, product or component operates as intended despite the presence of hardware or software faults. *

1	2	3	4	5
○	○	○	○	○

Recoverability - Degree to which, in the event of an interruption or a failure, a product or system can recover the data directly affected and re-establish the desired state of the system. *

1	2	3	4	5
○	○	○	○	○

Security

Degree to which a product or system protects information and data so that persons or other products or systems have the degree of data access appropriate to their types and levels of authorization.

Confidentiality - Degree to which a product or system ensures that data are accessible only to those authorized to have access. *

1 2 3 4 5

Integrity - Degree to which a system, product or component prevents unauthorized access to, or modification of, computer programs or data. *

1 2 3 4 5

Non-repudiation - Degree to which actions or events can be proven to have taken place so that the events or actions cannot be repudiated later. *

1 2 3 4 5

Accountability - Degree to which the actions of an entity can be traced uniquely to the entity. *

1 2 3 4 5

Authenticity - Degree to which the identity of a subject or resource can be proved to be the one claimed. *

1 2 3 4 5

Maintainability

The degree of effectiveness and efficiency with which a product or system can be modified to improve it, correct it or adapt it to changes in environment, and in requirements.

Modularity - Degree to which a system or computer program is composed of discrete components such that a change to one component has minimal impact on other components.

1	2	3	4	5
○	○	○	○	○

Reusability - Degree to which an asset can be used in more than one system, or in building other assets. *

1	2	3	4	5
○	○	○	○	○

Analyzability - Degree of effectiveness and efficiency with which it is possible to assess the impact on a product or system of an intended change to one or more of its parts, or to diagnose a product for deficiencies or causes of failures, or to identify parts to be modified. *

1	2	3	4	5
○	○	○	○	○

Modifiability - Degree to which a product or system can be effectively and efficiently modified without introducing defects or degrading existing product quality. *

1 2 3 4 5

Testability - Degree of effectiveness and efficiency with which test criteria can be established for a system, product or component and tests can be performed to determine whether those criteria have been met. *

1 2 3 4 5

Portability

Degree of effectiveness and efficiency with which a system, product or component can be transferred from one hardware, software or other operational or usage environment to another.

Adaptability - Degree to which a product or system can effectively and efficiently be adapted for different or evolving hardware, software or other operational or usage environments. *

1 2 3 4 5

Installability - Degree of effectiveness and efficiency with which a product or system can be successfully installed and/or uninstalled in a specified environment. *

1 2 3 4 5

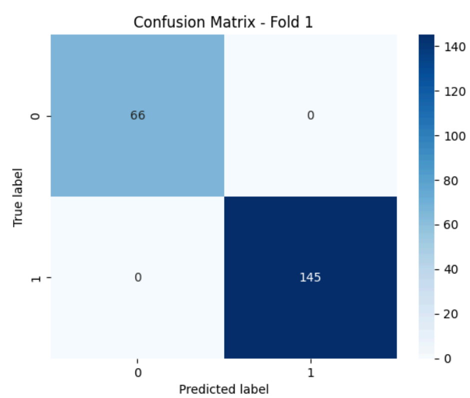
Replaceability - Degree to which a product can replace another specified software product for the same purpose in the same environment. *

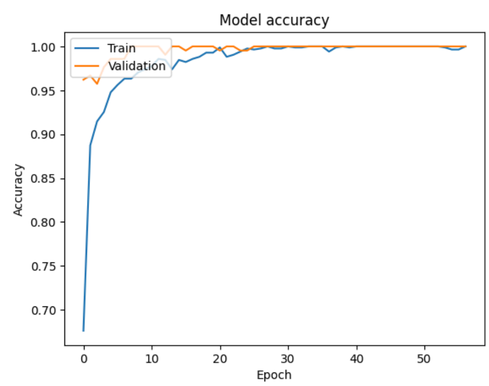
1 2 3 4 5

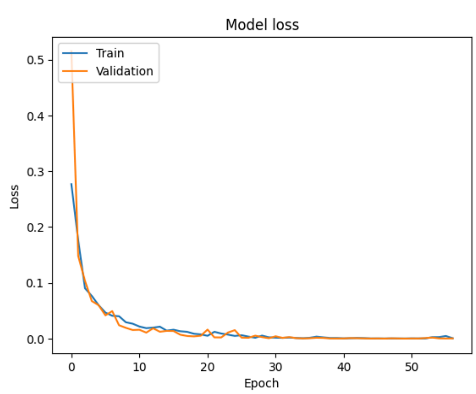
Appendix O- Results: Evaluation Data for CNN Model

5-Cross Fold Validation

```
Epoch 1/100
27/27 [==============================] - 1s 12ms/step - loss: 0.2769 - accuracy: 0.6762 - val_loss: 0.5150 - val_accuracy: 0.9621
Epoch 2/100
27/27 [==============================] - 0s 4ms/step - loss: 0.1769 - accuracy: 0.8873 - val_loss: 0.1482 - val_accuracy: 0.9668
Epoch 3/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0903 - accuracy: 0.9146 - val_loss: 0.1037 - val_accuracy: 0.9573
Epoch 4/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0766 - accuracy: 0.9253 - val_loss: 0.0674 - val_accuracy: 0.9763
Epoch 5/100
27/27 [==============================] - 0s 5ms/step - loss: 0.0600 - accuracy: 0.9478 - val_loss: 0.0600 - val_accuracy: 0.9858
Epoch 6/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0467 - accuracy: 0.9561 - val_loss: 0.0418 - val_accuracy: 0.9858
Epoch 7/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0410 - accuracy: 0.9632 - val_loss: 0.0494 - val_accuracy: 0.9858
Epoch 8/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0402 - accuracy: 0.9632 - val_loss: 0.0240 - val_accuracy: 1.0000
Epoch 9/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0294 - accuracy: 0.9703 - val_loss: 0.0194 - val_accuracy: 1.0000
Epoch 10/100
27/27 [==============================] - 0s 6ms/step - loss: 0.0268 - accuracy: 0.9739 - val_loss: 0.0155 - val_accuracy: 1.0000
Epoch 11/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0217 - accuracy: 0.9775 - val_loss: 0.0159 - val_accuracy: 1.0000
Epoch 12/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0188 - accuracy: 0.9858 - val_loss: 0.0108 - val_accuracy: 1.0000
Epoch 13/100
...
27/27 [==============================] - 0s 4ms/step - loss: 0.0047 - accuracy: 0.9964 - val_loss: 2.7777e-04 - val_accuracy: 1.0000
Epoch 57/100
27/27 [==============================] - 0s 4ms/step - loss: 6.6110e-04 - accuracy: 1.0000 - val_loss: 4.3924e-04 - val_accuracy: 1.0000
7/7 [==============================] - 0s 3ms/step
```

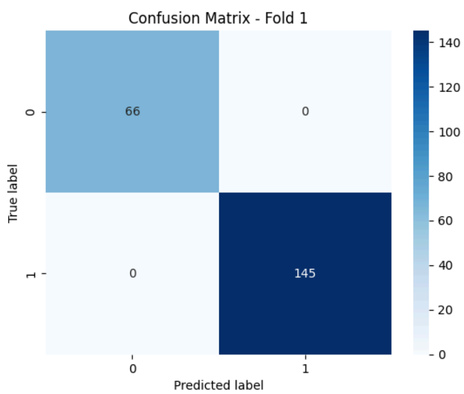


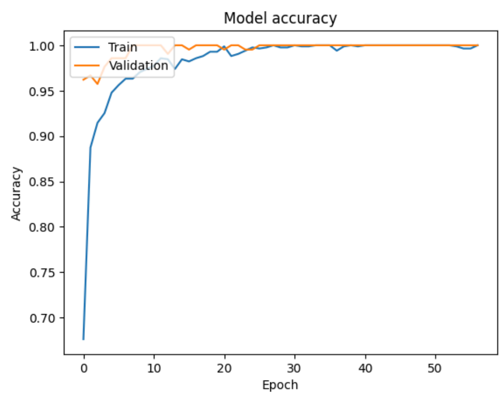


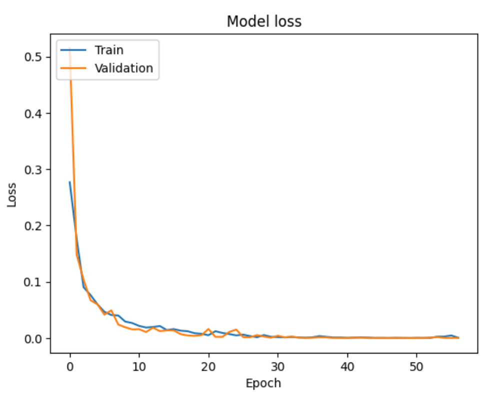



```
Fold 1:
Accuracy: 1.0
Specificity: 1.0
Sensitivity: 1.0
Confusion Matrix:
[[ 66   0]
 [  0 145]]
```

```
Epoch 1/100
27/27 [==============================] - 1s 10ms/step - loss: 0.2770 - accuracy: 0.7521 - val_loss: 0.5007 - val_accuracy: 0.9052
Epoch 2/100
27/27 [==============================] - 0s 5ms/step - loss: 0.1654 - accuracy: 0.9098 - val_loss: 0.1939 - val_accuracy: 0.9289
Epoch 3/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0822 - accuracy: 0.9205 - val_loss: 0.1795 - val_accuracy: 0.9194
Epoch 4/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0626 - accuracy: 0.9336 - val_loss: 0.1481 - val_accuracy: 0.9242
Epoch 5/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0532 - accuracy: 0.9514 - val_loss: 0.1416 - val_accuracy: 0.9242
Epoch 6/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0388 - accuracy: 0.9680 - val_loss: 0.1110 - val_accuracy: 0.9479
Epoch 7/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0325 - accuracy: 0.9656 - val_loss: 0.0902 - val_accuracy: 0.9668
Epoch 8/100
27/27 [==============================] - 0s 5ms/step - loss: 0.0250 - accuracy: 0.9810 - val_loss: 0.0822 - val_accuracy: 0.9621
Epoch 9/100
...
27/27 [==============================] - 0s 5ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss: 0.0171 - val_accuracy: 0.9953
Epoch 33/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0013 - accuracy: 0.9988 - val_loss: 0.0169 - val_accuracy: 0.9953
7/7 [==============================] - 0s 3ms/step
```

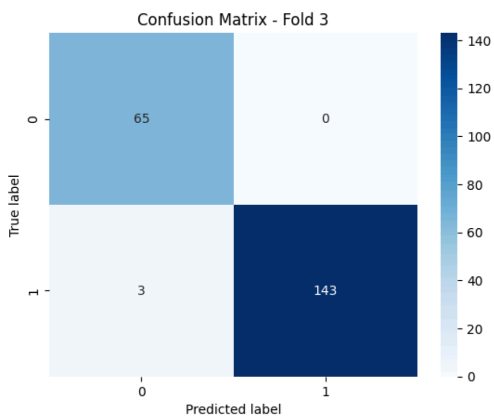


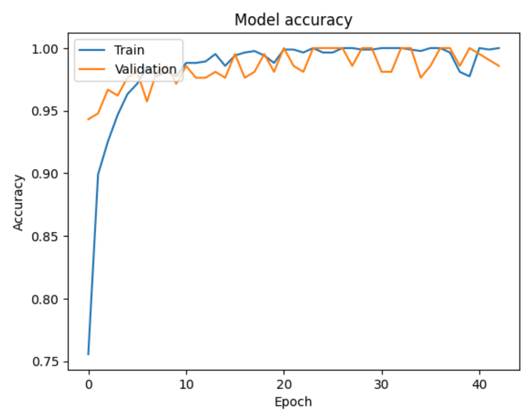


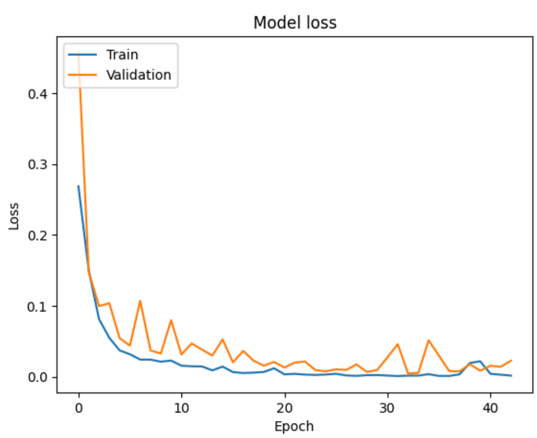



```
Fold 1:
Accuracy: 1.0
Specificity: 1.0
Sensitivity: 1.0
Confusion Matrix:
[[ 66   0]
 [  0 145]]
```

```
Epoch 1/100
27/27 [==============================] - 2s 11ms/step - loss: 0.2686 - accuracy: 0.7556 - val_loss: 0.4572 - val_accuracy: 0.9431
Epoch 2/100
27/27 [==============================] - 0s 4ms/step - loss: 0.1501 - accuracy: 0.8992 - val_loss: 0.1480 - val_accuracy: 0.9479
Epoch 3/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0814 - accuracy: 0.9253 - val_loss: 0.0997 - val_accuracy: 0.9668
Epoch 4/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0549 - accuracy: 0.9466 - val_loss: 0.1037 - val_accuracy: 0.9621
Epoch 5/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0372 - accuracy: 0.9632 - val_loss: 0.0544 - val_accuracy: 0.9763
Epoch 6/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0317 - accuracy: 0.9715 - val_loss: 0.0440 - val_accuracy: 0.9810
Epoch 7/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0242 - accuracy: 0.9846 - val_loss: 0.1071 - val_accuracy: 0.9573
Epoch 8/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0241 - accuracy: 0.9775 - val_loss: 0.0372 - val_accuracy: 0.9810
Epoch 9/100
...
27/27 [==============================] - 0s 4ms/step - loss: 0.0029 - accuracy: 0.9988 - val_loss: 0.0140 - val_accuracy: 0.9905
Epoch 43/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0016 - accuracy: 1.0000 - val_loss: 0.0228 - val_accuracy: 0.9858
7/7 [==============================] - 0s 2ms/step
```

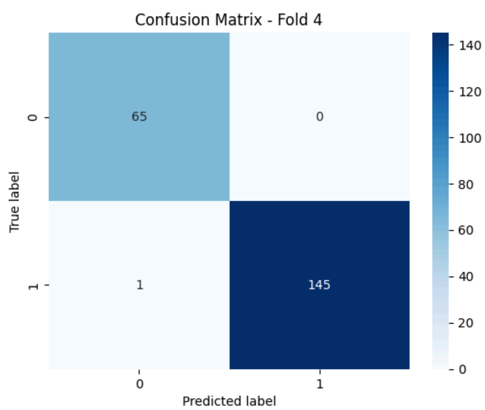


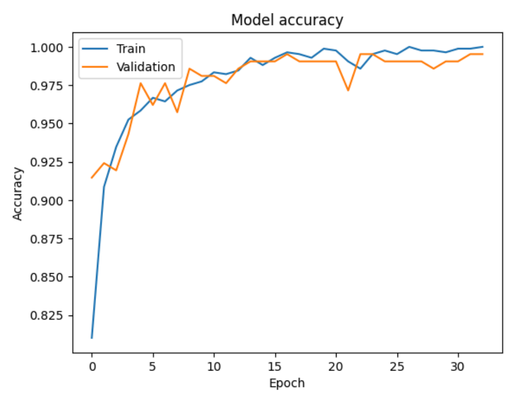


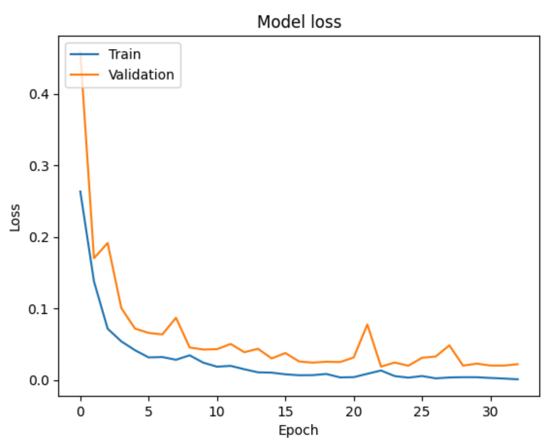



```
Fold 3:
Accuracy: 0.985781990521327
Specificity: 1.0
Sensitivity: 0.9794520547945206
Confusion Matrix:
[[ 65   0]
 [  3 143]]
```

```
Epoch 1/100
27/27 [==============================] - 1s 10ms/step - loss: 0.2635 - accuracy: 0.8102 - val_loss: 0.4583 - val_accuracy: 0.9147
Epoch 2/100
27/27 [==============================] - 0s 4ms/step - loss: 0.1378 - accuracy: 0.9087 - val_loss: 0.1703 - val_accuracy: 0.9242
Epoch 3/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0718 - accuracy: 0.9348 - val_loss: 0.1915 - val_accuracy: 0.9194
Epoch 4/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0540 - accuracy: 0.9526 - val_loss: 0.1006 - val_accuracy: 0.9431
Epoch 5/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0417 - accuracy: 0.9585 - val_loss: 0.0719 - val_accuracy: 0.9763
Epoch 6/100
27/27 [==============================] - 0s 3ms/step - loss: 0.0316 - accuracy: 0.9668 - val_loss: 0.0658 - val_accuracy: 0.9621
Epoch 7/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0321 - accuracy: 0.9644 - val_loss: 0.0638 - val_accuracy: 0.9763
Epoch 8/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0283 - accuracy: 0.9715 - val_loss: 0.0870 - val_accuracy: 0.9573
Epoch 9/100
...
27/27 [==============================] - 0s 4ms/step - loss: 0.0021 - accuracy: 0.9988 - val_loss: 0.0202 - val_accuracy: 0.9953
Epoch 33/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss: 0.0221 - val_accuracy: 0.9953
7/7 [==============================] - 0s 3ms/step
```

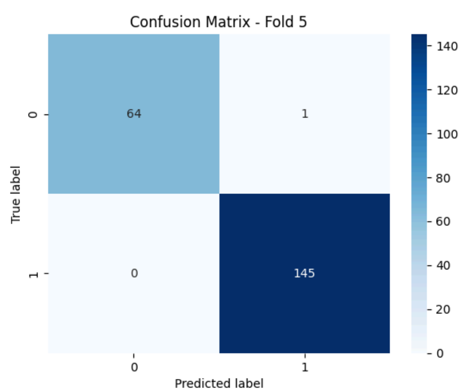


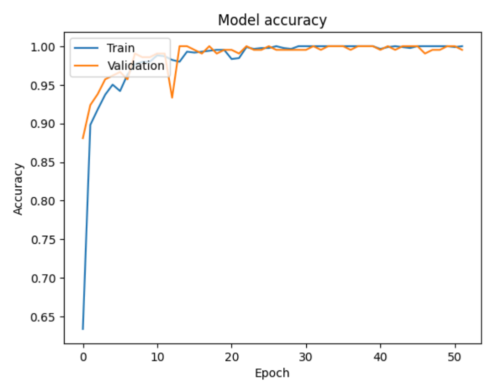


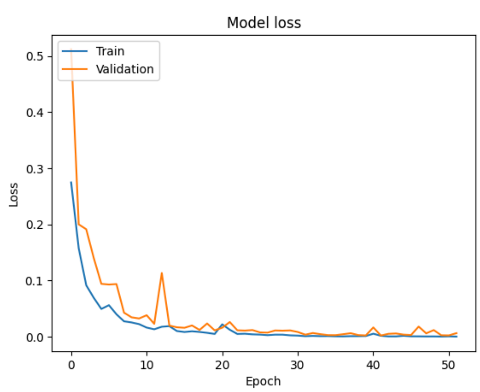



```
Fold 4:
Accuracy: 0.995260663507109
Specificity: 1.0
Sensitivity: 0.9931506849315068
Confusion Matrix:
[[ 65   0]
 [  1 145]]
```

```
Epoch 1/100
27/27 [==============================] - 1s 9ms/step - loss: 0.2749 - accuracy: 0.6339 - val_loss: 0.5119 - val_accuracy: 0.8810
Epoch 2/100
27/27 [==============================] - 0s 3ms/step - loss: 0.1578 - accuracy: 0.8981 - val_loss: 0.2002 - val_accuracy: 0.9238
Epoch 3/100
27/27 [==============================] - 0s 3ms/step - loss: 0.0917 - accuracy: 0.9182 - val_loss: 0.1915 - val_accuracy: 0.9381
Epoch 4/100
27/27 [==============================] - 0s 3ms/step - loss: 0.0693 - accuracy: 0.9372 - val_loss: 0.1401 - val_accuracy: 0.9571
Epoch 5/100
27/27 [==============================] - 0s 3ms/step - loss: 0.0496 - accuracy: 0.9502 - val_loss: 0.0943 - val_accuracy: 0.9619
Epoch 6/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0563 - accuracy: 0.9419 - val_loss: 0.0931 - val_accuracy: 0.9667
Epoch 7/100
27/27 [==============================] - 0s 5ms/step - loss: 0.0401 - accuracy: 0.9633 - val_loss: 0.0939 - val_accuracy: 0.9571
Epoch 8/100
27/27 [==============================] - 0s 4ms/step - loss: 0.0276 - accuracy: 0.9763 - val_loss: 0.0430 - val_accuracy: 0.9905
Epoch 9/100
...
27/27 [==============================] - 0s 4ms/step - loss: 7.9327e-04 - accuracy: 0.9988 - val_loss: 0.0025 - val_accuracy: 1.0000
Epoch 52/100
27/27 [==============================] - 0s 4ms/step - loss: 3.6562e-04 - accuracy: 1.0000 - val_loss: 0.0065 - val_accuracy: 0.9952
7/7 [==============================] - 0s 3ms/step
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```








```
Fold 5:
Accuracy: 0.9952380952380953
Specificity: 0.9846153846153847
Sensitivity: 1.0
Confusion Matrix:
[[ 64   1]
 [  0 145]]
```

Appendix P- Results: ISO/IEC 25010 Evaluation

Respondent	**Field**
1	Information Technology
2	Information Technology
3	Information Technology
4	Information Technology
5	Consultant Pediatrician
6	Doc Mendoza
7	Doc Gallinero
8	Dr Chua
9	Parent
10	Parent
11	Guardian
12	Guardian

Characteristic	Respondent												Mean	Overall Mean
	1	2	3	4	5	6	7	8	9	10	11	12		
Functionality Stability														
1. Functional Completeness	5	4	5	5	4	4	4	3	5	5	5	4	4.416666667	4.305555556
2. Functional Correctness	5	5	4	5	4	3	3	3	4	5	5	5	4.25	
3. Functional Appropriateness	4	4	5	5	4	3	4	3	4	5	5	5	4.25	
Performance Efficiency														
1. Time Behavior	4	4	4	5	5	4	5	5	5	5	5	5	4.666666667	4.638888889
2. Resource Utilization	5	5	5	5	5	3	5	5	4	5	4	5	4.666666667	
3. Capacity	5	5	5	5	5	3	4	5	4	5	5	4	4.583333333	
Compatibility														
1. Co-existence	4	4	5	5	4	3	4	5	5	4	5	5	4.416666667	4.291666667
2. Interoperability	5	5	1	5	4	3	4	5	4	4	5	5	4.166666667	
Usability														
1. Appropriateness	5	5	5	5	4	4	4	5	5	5	5	4	4.666666667	4.513888889
2. Learnability	5	5	5	5	5	4	4	5	4	5	5	5	4.75	

3. Operability	5	5	5	5	5	4	4	5	4	5	5	5	4.75	
4. User Error Protection	4	5	3	5	4	3	3	5	5	5	4	5	4.25	
5. User Interface Aesthetics	5	5	4	5	4	4	3	4	5	5	5	5	4.5	
6. Accessibility	5	5	3	5	4	4	3	4	4	5	4	4	4.166666667	
Reliability														
1. Maturity	5	4	4	5	5	4	4	4	4	5	4	5	4.416666667	4.416666667
2. Availability	5	4	5	5	5	5	4	5	5	5	4	5	4.75	
3. Fault Tolerance	4	4	4	5	4	5	4	5	3	5	4	5	4.333333333	
4. Recoverability	4	4	2	5	3	5	4	5	5	5	4	4	4.166666667	
Security														
1. Confidentiality	5	5	5	5	4	4	4	5	5	5	5	5	4.75	4.283333333
2. Integrity	5	5	1	5	3	4	4	5	4	5	5	5	4.25	
3. Non-repudiation	4	4	1	5	3	4	4	4	4	5	5	5	4	
4. Accountability	4	4	1	5	4	4	5	5	4	5	5	5	4.25	
5. Authenticity	4	4	1	5	3	4	5	5	4	5	5	5	4.166666667	
Maintability														

1. Modularity	5	4	3	5	3	4	4	5	4	5	4	4	4.166666667	4.416666667
2. Reusability	5	5	4	5	4	4	4	5	5	5	4	5	4.583333333	
3. Analyzability	5	5	4	5	3	4	4	5	5	5	4	5	4.5	
4. Modifiability	4	5	2	5	4	4	4	5	5	5	4	4	4.25	
5. Testability	5	5	5	5	3	4	4	5	4	5	5	5	4.583333333	
Portability														
1. Adaptability	5	5	3	5	4		4	5	4	5	5	5	4.545454545	4.393939394
2. Installability	5	4	1	5	4		4	5	4	5	5	4	4.181818182	
3. Replaceability	5	5	4	5	4		4	5	4	4	5	4	4.454545455	
OVERALL														**4.407575758**

Appendix Q - Transcript of Consultation with Developmental Pediatrician (Domain Expert)

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COLLEGE OF INFORMATION AND COMMUNICATIONS TECHNOLOGY
Luna St., La Paz, Iloilo City 5000
Iloilo, Philippines
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* Website: www.wvsu.edu.ph * Email Address: cict@wvsu.edu.ph

The following transcripts captures the insightful discussion held on dates, April 17, 2023 and May 29, 2023 during the consultations between the student researchers of "AutiCheck: ASD Screening Tool For Toddlers Using Convolutional Neural Networks" and the esteemed domain expert, Dr. Celina Cordero-Gellada in the context of the related research. The purpose of the following two meetings was to seek valuable guidance and expertise from the domain expert, ensuring the research aligns with industry standards and best practices.

This document serves as a crucial component in validating the depth of engagements with the domain expert. It will be appended to the research as part of the appendices, offering tangible evidence of the collaboration. The transcripts include a comprehensive record of the discussions, insights, and recommendations shared during the consultation, providing transparency and accountability in the research process.

To further authenticate this interaction, the document concludes with a signature obtained from the domain expert, symbolizing their endorsement and acknowledgment of the consultation's content and relevance to the research endeavor.

DR. CELINA CORDERO-GELLADA
VP for Medical and Allied Sciences
West Visayas State University

Domain Expert

Appendix R - Disclaimer

Disclaimer

This thesis project, titled 'AutiCheck: An ASD Screening Tool for Toddlers Using Convolutional Neural Networks,' is being submitted to fulfill the requirements for the Bachelor of Science in Computer Science degree at the College of Information and Communications Technology, West Visayas State University. The software and accompanying documentation represent our original work, with the exception of the questionnaire content sourced from the 'Q-CHAT-10,' a toddler ASD screening tool developed by Allison et al. (2012). The questionnaire comprises ten questions assessing the child's behavior, identified by the aforementioned authors as indicative of ASD symptoms.

We hereby authorize the College of Information and Communications Technology to utilize, publish, reproduce, or distribute the software project and its documentation, either in whole or in part, in local or international journals/conferences, provided proper acknowledgment is given.

Eunice D. Bagsit

Maria Joeanne A. Gison

Mayenel O. Quintilla

Kenji John B. Sondia

Kim Jasper T. Tenan

April 2024