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Intelligent Mobile Application for Autism Detection and Level Identification System Using Deep-Learning Model

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ABSTRACT

The early detection and level assignment are very important in autism spectrum disorder (ASD) cases. In this paper, we introduce an autism diagnosing and level identification mobile application based on a deep-learning model. The application is designed with two stages; the first stage classifies children as either ASD children or potentially normal, while the second stage identifies the ASD level. For feature extraction and image classification, a convolutional neural network (CNN) is proposed. The 2,122 photos that were removed from the 3000 original dataset because of poor quality and racial imbalances made up the dataset used to develop and evaluate this model. Results show that the accuracy is 97.3% and the area under the curve is 99.8%. The identification of ASD level is performed using two well-defined scales in the literature that are adopted in the traditional examinations. Depending on the child's ASD level, psychiatrists provide specific and standard learning support. The application provides caregivers with fast decisions (about 20 minutes) to get an idea of the learning strategy to be followed with their child. Early intervention is very beneficial for children diagnosed with ASD, and these applications assist children in underfunded nations or those without access to healthcare.

1. INTRODUCTION

The term ASD describes a category of serious neurodevelopmental brain disorders, including autism, Asperger's syndrome, and childhood disintegrative disorders. As the name "spectrum" suggests, there can be significant variation in the severity and symptomatology of many diseases [1]. The International Statistical Classification of Diseases and Related Health Problems now classify these diseases as Pervasive Developmental diseases under Mental and Behavioral Disorders (MBD) [2]. Most commonly, between the ages of three and six, early signs of ASD manifest. These might include not making eye contact, showing little interest in caregivers, and being unable to react appropriately when called names [3]. These disorders also affect how a person perceives and interacts with other people; throughout their early years of life, they struggle to socialize and communicate with society, and they might suddenly become reclusive or angry. Even if ASD initially appears in infancy, it frequently continues throughout adolescence and maturity [4]. The patient's dataset is significant, where data mining is crucial for figuring out the classification strategy for sickness classification and prediction in the medical field. The precision of the dataset and the machine learning methods employed in its classification determine the likelihood of a disease [5, 6]. There are some disruptive behaviors in children with ASDs. They usually aren't able to talk well. Instead, they establish relationships using pointing words and gestures. Thus, one of the hardest things for caretakers to do is to comprehend their demands; nevertheless, this effort may be greatly facilitated by an early diagnosis. Assistive technology and the Internet of Things (IoT) can eliminate the absence of verbal and nonverbal interactions [7, 8].

Computer systems with human-like visual perception skills are made possible through the use of computer vision. It is an interdisciplinary field that gives computer systems the ability to precisely interpret, evaluate, and comprehend their visual surroundings. Computer vision, for instance, allows machines to identify significant information from pictures and movies in an approach that is comparable to that of people. Giving computers this "natural" visual appearance is meant to enable them to comprehend and evaluate intricate digital systems on pace with, if not superior to, human cognition. The field of machine learning, which is focused with "teaching" machines new abilities over time, is used in modern computer vision. As opposed to a system that consistently chases a predefined set of guidelines or directives, a machine learning system may take past experiences and judgments into account to identify the best course of action. Moreover, all of this can be completed with little to no assistance from humans [9, 10].

Within the field of artificial intelligence (AI), deep learning (DL) is a subset of machine learning. Digital data may now be analyzed and understood by machines without the assistance of humans. Deep learning frequently uses both statistical concepts and algorithms to build models that can make decisions based on incoming data. Consequently, Applications of deep learning are found in many fields, ranging from advanced software engineering to supercomputers [11, 12].

Haque and Valles [13] modified the Facial Expression Recognition (FER) 2013 dataset in 2018 to better identify the facial emotions of children with autism. They used deep learning techniques to do this. Parikh et al. [14] developed a system that uses machine learning techniques to distinguish between the symptoms of autism. Recurrent neural networks and Convolutional neural networks in particular are DL techniques that have been suggested or used to identify autism in youngsters [15, 16]. As such, it is imperative that every household supports early intervention for children with ASD. This entails creating an impartial, reasonably priced, and easily comprehensible diagnosis or screening method.

The majority of people's everyday activities in the modern digital age revolve around mobile apps. social media, entertainment, and business to productivity. Our interactions with technology are greatly aided by smartphone applications. Creating software, especially for smartphones and digital assistants, is defined as mobile application development. Developing mobile apps is a complicated development process that demands skills in fields like designing the user interface, programming, testing, and deploying the application. As the usage of mobile devices is increasing in today's world, mobile application development is too growing and demands highly skilled talent and many companies look to different fields from healthcare or medical professionals, retail, telecommunications, and e-commerce to insurance etc. [17, 18]. Mobile applications offer a smoother, more streamlined experience compared to mobile websites. They load faster, provide intuitive navigation, and offer offline access to content, enhancing the overall user experience [19]. In contrast to websites, which typically require web servers, applications on mobile devices often keep their data locally. Because of this, data retrieval in mobile applications occurs quickly [20, 21]. Additional technologies can improve the life of an ASD kid. Making use of deep learning and machine learning techniques, for instance, IoT-based devices can diagnose and improve the quality of life for patients [7, 22].

In this study, a mobile application (and PC-GUI applications) is introduced with two stages. The first stage diagnoses ASD children from their faces and the second stage identifies the level or class of ASD. utilizing a 97.3% accurate DL model that we constructed, the ASD diagnostic stage classifies children as potentially autistic or healthy. The model is trained and tested using a dataset that is available in the Kaggle repository. The dataset used to assess these models is made up of photos that have been enhanced via image processing and then divided evenly between autistic and non-autistic children. Of it, 85% is allocated for teaching, while the remaining 15% is utilized for testing and validation. The level identification stage is performed with a standard questionnaire and rating scale to who takes care of ASD children. The level identification result can surely draw road map for parents to follow the specific learning strategy that assigned by specialist or professionals to overcome or decrease ASD symptoms. This categorization technique bridges high accuracy, usability, and quickness to support autistic children in need of early intervention.

2. RELATED WORK

In recent times, researchers have concentrated on employing cutting-edge artificial intelligence (AI) approaches to diagnose autism in children. Experts are able to diagnose the illness in children based only on picture analysis because of the distinct facial deformities that sufferers share [23]. Based on this, the authors [24, 25] created a 94.6% accurate DL model to categorize kids as either healthy or probably autistic. Three thousand photos were utilized to train and test the model, with 90% of the data going toward training and 10% going toward testing. The images were split evenly between children with autism and those without. In order to identify autistic children in the early stages, Akter et al. [26] submitted an improved structure for autism face identification based on a transfer-learning approach. Using a range of ML and DL classifiers along with other transfer-learning based pretrained models, face Images of autistic children were gathered from the Kaggle data archive. The 90.67% was determined to be the best accuracy. The authors employed the identical dataset that was utilized by Mujeeb Rahman and Subashini [23].

However, in a study published by Alkahtani et al. [27], a range of transfer learning techniques are seen in deep CNNs to identify children with autism through facial landmarks. The best settings for the CNN model's optimizer and hyperparameters are determined empirically in order to increase accuracy. Machine learning algorithms, including logistic regression, a linear support vector machine (linear SVC), random forest, decision tree, gradient boosting, MLPClassifier, and K-nearest neighbors, are utilized with a transfer learning technique, such as MobileNetV2 and hybrid VGG19. Analyze the deep learning models on a regular Kaggle research dataset. On the test set, the MobileNetV2 model's accuracy was 92%. The suggested research's findings show that the most effective transfer learning techniques are those using MobileNetV2. Subgroups of autism spectrum disorder decision trees predict adaptive behavior and autism severity trajectories in children with ASD. A cross-sectional study employing a regression tree technique and a classification algorithm was recently conducted on the PDD Behavior Inventory (PDDBI) data. In the end, three behaviorally different subgroups of ASD were identified using the Autism Spectrum Disorder-Decision Tree, or ASD-DT: minimally verbal, verbal, and atypical [28, 29].

An empirical investigation was conducted using the CNN model to identify the ideal optimizer and hyperparameter set for enhancing the accuracy of the predictions [30]. After training and verifying using the ideal setup, the modified models, Xception showed an accuracy of 95%, VGG19 reached 86%, ResNet50V2 with 94%, MobileNetV2 obtained 92%, and EfficientNetB0 with 85.8. models of Classification utilizing OpenCV and the VGG16 technique of SVM classifier, CNN, and Haar Cascade were the main emphasis [31]. The accuracy findings with these models were: Convolution Neural Network (VGG16) / 90%, Support Vector Machine / 65%, and Haar Cascade Classifier / 72%. The goal of the author's novel approach to kid-face photo-based autism identification in children was to identify autistic children's faces from typical children's faces by utilizing a deep learning model to retrieve face characteristics [32]. The input face images are effectively classified by the proposed dense net-based deep learning architecture. Increasing the overall accuracy of the system requires a dense block. The proposed model had a 91.50% classification accuracy.

Advances in technology and mobile application-based helping systems is presented. Emerging development in mobile helping and technology has offered a viable opportunity for help families or parents. Researchers have slowly found that phones can be turned into helping tools. For instance, in order to eliminate the time-consuming and costly ASD diagnostic techniques, The ASDTest app, a smartphone-based ASD monitoring tool, was created by the authors [33]. Over 1400 incidents were recorded by the app, including ones involving adults, teens, toddlers, and newborns. Health providers can utilize the proposed ASDTests app to support their practice or to advise patients about whether to seek a formal clinical diagnosis. The toddler data set's irregular structure makes it difficult to identify disorders in that class. The app contains four different tests and is available in 11 different languages. Prottoy is a mobile interactive application that was created by researchers [34] to assess children with autism between the ages of 3 and 11. Translating it into Bengali required adhering to cross-cultural validation standards. Therefore, by comprehending the scenarios included in each question, parents may quickly assess if their child has autism. Following screening, this software automatically modifies user responses to identify whether a child may have autism. We anticipate that this software will assist in early autism detection in Bangladeshi children. On the other hand, the author suggests a mobile application for screening for autism spectrum disorders that is sensitive to cultural differences. A symptom checklist with clinical validation and an advanced machine learning model are combined in the recommended application to track and identify autism spectrum disorder in low- and middle-income countries for the first time. After training machine learning models with clinical pictorial autism assessment schedule data and assessing their predictive performance, the random forest classifier (area under the receiver operating characteristic: 0.98) proved to be the most effective one to include in the mobile screening tool. A significant portion of the graphical autism assessment schedule questions are superfluous, as shown by feature selection, and they might be removed to expedite the screening process [35].

In terms of predicting autism features across various age groups, the study did not come to any firm conclusions. To that end, their goals are to create a mobile application that can be used by anyone to identify ASD and offer a practical prediction model built on machine learning methods. Resulting of this investigation, Random Forest-CART (Classification and Regression Trees) and Random Forest-ID3 (Iterative Dichotomiser 3) were created, along with a mobile application based on the suggested prediction model were integrated into the construction of an autism prediction model. 250 genuine datasets, gathered from autistic and non-autistic individual's symptoms, further to the AQ-10 dataset, which was employed to evaluate the proposed model. The prediction models were trained using the AQ-10 dataset, and because surveys were employed to collect the actual data, it's possible that respondents weren't honest enough to supply the correct information, which explains why the real dataset performs comparably worse [36].

3. PROPOSED INTELLIGENT APPLICATION

The proposed autism diagnosing and level identification application with the deep-learning model is explained in this section. The purpose of the subsections in this part is to provide the reader with a clear understanding of the concept underlying the suggested application.

3.1 Suggested model for deep learning

CNNs, or convolutional neural networks are developed from Multi-Layer Perceptron (MLPs) and used in deep-learning methods with a high degree of fabric depth. Therefore, it is efficient for classifying image data [37, 38]. The suggested CNN model, which is based on DL, uses computer vision to identify autistic children by taking into account their shown ability to discriminate well while retaining high-performance levels. The CNN algorithm excels in processing and identifying pictures. Among the layers that comprise this structure in the suggested model are the fully connected layers, pooling layers, and convolutional layers. To be more precise, as Figure 1 explains, the proposed DL model is constructed using three convolutional layers and max-pooling layers appended to a flattened and fully connected layer.

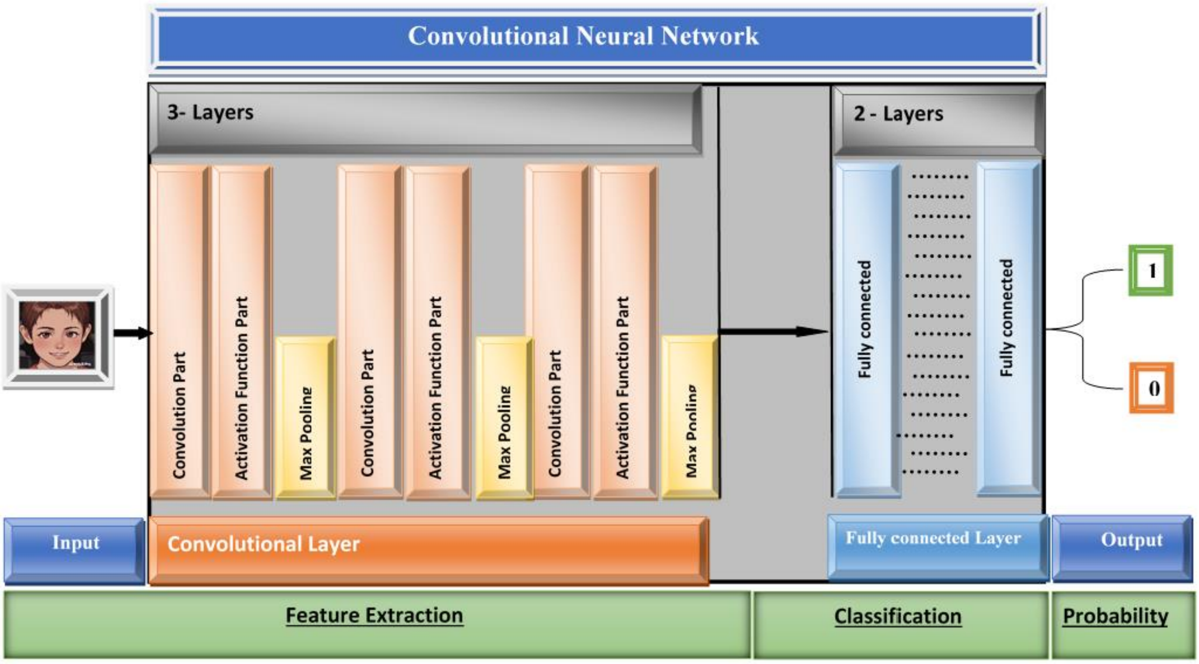

Figure 1. The proposed structure of the autism DL-classifier model

Although it is well known that the algorithm itself initializes and updates the network parameters (weights and bias values), there is an issue with the hyperparameters setting that, when properly selected, can improve model performance. The model hyperparameters that were determined after several attempts are explained in Table 1.

Table 1. Architecture and hyperparameters of the model

Model Architecture & Hyperparameters	
Input Layer	shape=(400,400,3)
Conv layer1	Conv2D, f=16, s=1, p=same
Pooling Layer	MaxPooling2D
Conv Layer2	Conv2D, f=32, s=1, p=same
Pooling Layer	MaxPooling2D
Conv Layer3	Conv2D, f=256, s=1, p=same
Pooling Layer	MaxPooling2D
Activation Layer	ReLU
FC Layer	
Dense Layer	512 – ReLU
Dense Layer	1 – sigmoid
Optimizer	Adam
No. Of Epochs	40
Learning Rate	0.0001

To train and test the proposed model, a specific set of training and validation pictures must be used. Subsequently, as seen in Figure 2, the model is tested on a set of previously unseen images (test images) to determine its effectiveness. While test images are label-free, training and validation datasets have labels that unambiguously indicate the kind of image—autistic or non-autistic—that it belongs to. Important features that were extracted from the training images are retained by the machine learning model that has been trained. It can accurately forecast the category of any new or unknown data using this knowledge.

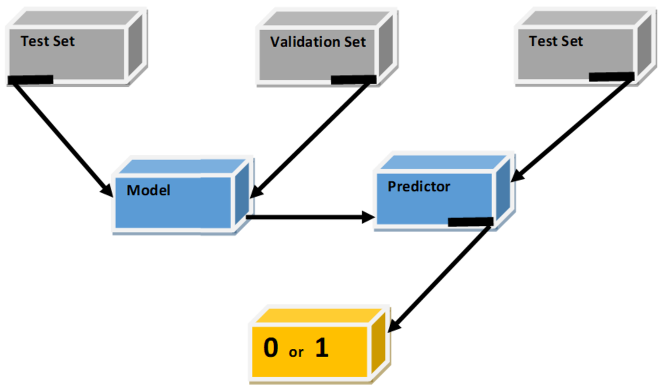

Figure 2. DL model training, validation, and testing

Figure 3 demonstrates the process of the suggested method for diagnosing autism, which classifies patient faces using the DL model. Where obtaining a dataset is the initial step in applying DL for ASD detection, if at all feasible, to gather a substantial amount of pertinent data, such as patient images to support superior results. Dataset Cleaning is to remove any poor quality images, extracting unneeded image extensions, duplication has already been eradicated, excluding unwanted races to support specific Dataset attributes. This stage involves transforming the data into a format that enhances training efficacy and can be processed by models. The photographs in the dataset need to be augmented. This may be done by zooming, flipping the data horizontally, and applying rotation to create a better collection of images for the training and validation sets. In addition, resizing the photographs in the collection is necessary to guarantee their compliance with the designated architecture. 85% of the preprocessed dataset is used for training, 10% is used for validation, and 5% is used for testing.

Accurate diagnostic prediction from the input data is the aim of the model's training. To generate a well-trained and verified DL model, many functions are employed during the training process. Validation involves testing the model on a different set of data and comparing the outcomes to real diagnoses in order to assess the model's performance. This procedure contributes to the assessment of the DL-based diagnostic system's precision and dependability. Finally, the Model will be able to classify the input depending on features that it extracted in the process.

Figure 3. Proposed DL model workflow

3.2 Adopted dataset structure

Approximately 3,000 evenly distributed face photos of autistic children and non-autistic make up the approved Kaggle dataset [39]. There were 3014 photos in the original dataset [40], all of which had obvious problems as research [41] shown. All of the photographs in the Kaggle dataset are accessible online since the contributor said that he was unable to secure any ASD images from organizations or reliable sources [41]. Our preferred dataset, reference [39], comprises 89% White children and 11% children of color. The purpose of this dataset is to showcase the impact of face image-based deep learning progress. The racial details in the ASD dataset are displayed in Table 2.

Table 2. The proportion of race in the ASD dataset

Dataset	**East-Asian Child**	**Black Child**	**White Child**	**Other**
Kaggle ASD dataset	1.10%	4.20%	89%	5.70%

The many races with low ratios and a few more low-quality photos have been tried to be excluded. So, 2000 photos are used to perform argumentation tasks using a balanced dataset, meaning that each category of picture has an equal amount of photographs. Training, validation, and testing groups are formed by separating the data. Of the total facial pictures, the training set comprises 85%, while each validation and testing dataset group has 15% (a total of 10% and 5%, respectively).

3.3 Mobile and PC-GUI application

The proposed ASD mobile application is applicable on mobile and even on PC due to the used of Flutter software environment to build the application with the same procedure and stages. The suggested mobile application block design is explained in Figure 4, which also depicts the application's workflow in the two stages of diagnosing autism and determining its severity.

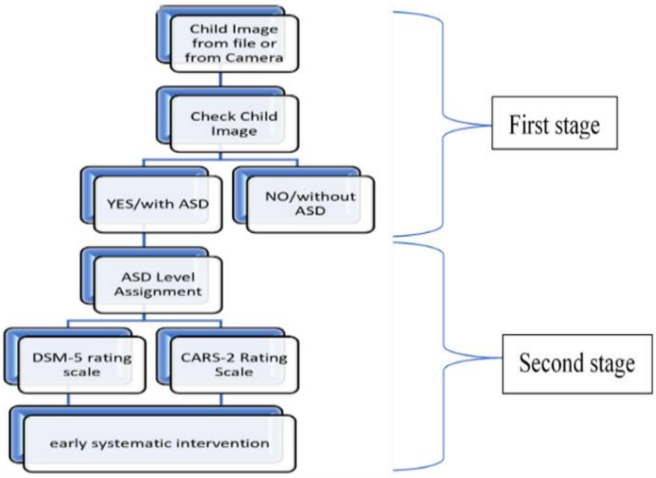

Figure 4. Mobile application block diagram

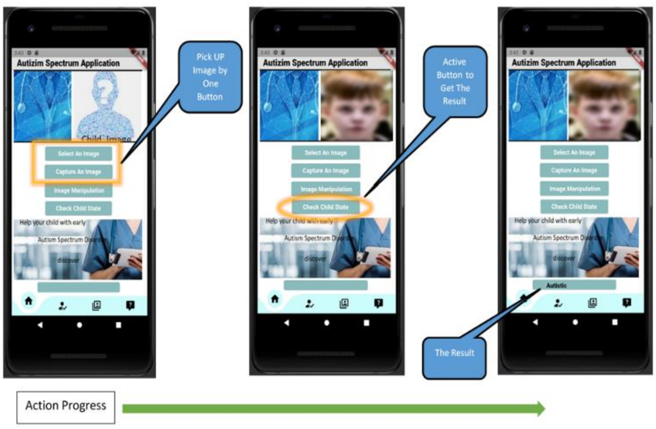

Figure 5. Steps sequence for first interface (Home Page)

The application started with the first stage getting a child image with two options. The first option is getting child image from mobile gallery or PC-saved folder and second option to capture image with mobile Cramer or PC web-cam. The DL model that we built classifies the child's face image and decides if the child suffering from ASD or not. Figure 5 illustrates how the user's selections on the home page allow them to obtain the underlying child picture. These options are based on delivering the image either from a gallery or capturing an image using a mobile or PC camera by selecting the related button. After that, we click on the check button to get the result depending on the DL model features analysis. The steps sequence of the testing process are explained in Figure 5.

It is important to mention here that we added an optional button, especially for the PC-GUI app as this app will use a PC webcam, and as we know it has lower specs or resolution than a mobile camera. This button is used for face detection and tries to crop the other unneeded things surrounding the child's face (focus on the child's face). This button is shown in Figure 6.

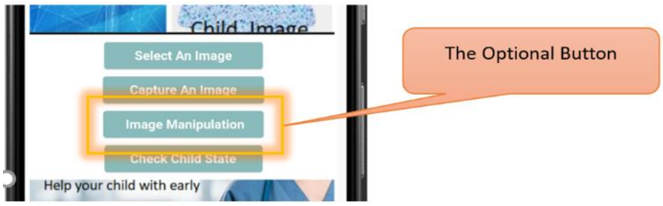

Figure 6. The optional button

Table 3. Explain each level with related points

Severity Level	Social Affective	Restricted and Repetitive Behaviors
Level 1. "Needing assistance"	In the absence of support, deficits in social communication lead to visible impairments in the absence of assistance. Initiating social connections can be challenging, and there should be clear examples of abnormal or ineffective responses to others' advances. Could seem less interested in interacting with others.	Behavior that is rigid interferes seriously with one's ability to perform in one or more situations. It is hard to switch between tasks. Planning, organization, and independence-impeding problems.
Level 2. "Needing substantial assistance"	Substantial deficits in verbal and nonverbal social communication skills. Social deficiencies are noticeable even when help is available. Reduced or unusual reactions to social advances made by others, as well as limited social engagement initiation.	Behavior that is rigid and repetitious, inflexible, or difficult to adjust to change manifests itself often enough to be noticed by the untrained eye and makes it hard to perform in a variety of situations. unhappiness and/or trouble shifting one's focus or direction.
Level 3: "Needing very substantial assistance"	Severe functional impairments, a restricted ability to initiate social relationships, and a low reactivity to social approaches from others are all results of severe abnormalities in verbal and nonverbal social communication abilities.	Extremely rigid conduct, a strong inability to adapt to change or other confined and repeated activities significantly impair performance in all domains. extreme anxiety or difficulty shifting one's attention or course of activity.

The second stage completes the first stage by containing two scales of identify ASD level/severity. The parents or care-givers opinion, can chose anyone as they see it suitable and easy for them. The obtained result helps families to go earlier with correct standard intervention strategies assigned by specialists and professionals to be followed with ASD children. The two most often used diagnostic tools for autism spectrum disorders are the Childhood Autism Rating Scale (CARS) and the DSM-5. There are several more tools available as well. Table 3, provides an overview of the severity rating methodology that was adopted with the DSM-5. The severity assessment takes into account the individual's needs for services as a result of the impairment caused by the ASD symptoms. In clinical settings, severity rating frequently captures the effects of cognitive limitations, but it is not yet a measurable score that can be used to track improvement [42]. Published measures aim to quantify the intensity of core symptoms [43, 44], and enable assessment of intervention-induced improvement [45]. Here we have two sides, social affective side and restricted or repetitive behaviors side. Each side has related questions to be answered by the caregiver.

This scale is represented in our application by a checklist and depending on checked boxes the result is calculated. The obtained results refer to the autism level as explained in Figure 7. The mentioned scale can be reached by touching the second navigation button. The working steps for using this type of level identification are illustrated in Figure 8.

Figure 7. First scale navigation button

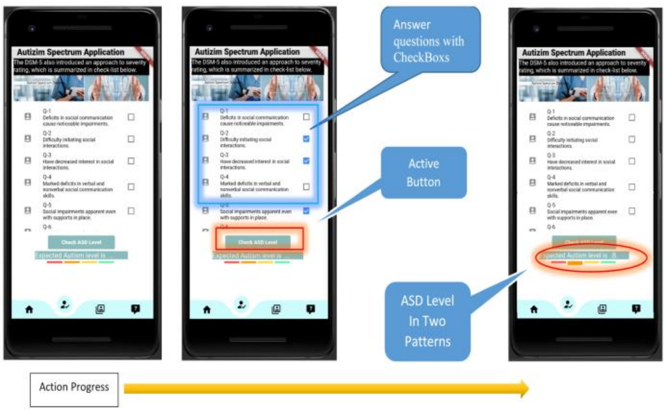

Figure 8. Steps sequence for the second interface

At the other hand, the CARS uses 15-item rating scales completed by the clinician or caregivers that comprise the following: visual response, listening, olfactory-taste and tactile senses, fear and anxiety, verbal and nonverbal communication, thinking, intelligence, emotional expression and regulation, relationships with others, physical use, using objects in the game, adapting to change-limited interests, and each point has four sub-questions [46]. Utilizing a scale where 1 represents normalcy, 2 represents mild abnormality, 3 represents moderate abnormality, and 4 represents severe abnormality, CARS-2 asks the child's main healthcare provider, a teacher, or a parent to score the child's behaviors. A score of 30 indicates mild autism on the scale, which ranges from 15 to 60. Severe autism is indicated by scores between 37 and 60, whereas mild to moderate autism is suggested by scores between 30 and 36.5. Scale Severity groups as shown in Table 4. Each item in the CARS-2 model includes a 7-point type scale with allowable ratings for each item as shown in Table 5.

Table 4. Scores range and severity group

Severity Group	Range
Minimal to Nonexistent ASD Symptoms	(15 – 29.5)
Moderate to Mild ASD Symptoms	(30 – 36.5)
Extreme ASD Symptoms	(37 and higher)

Table 5. 7-point type scale

	Seven Allowable Ratings for Each Item
1	Within typical bounds for that age group.
1.5	Very mildly unusual for that age group.
2	Mildly unusual for that age group.
2.5	Mildly-to-moderately unusual for that age group.
3	Moderately unusual for that age group.
3.5	Moderately-to-extremely unusual for that age group.
4	Extremely unusual for that age group.

In the proposed application, Figure 9, shows the third interface that is specified for CARS-2, which can reach it by touch navigation button. With this interface, the user can apply the CARS-2 scale by choosing values per item, the steps sequence is explained in Figure 10.

Figure 9. Second scale navigation button

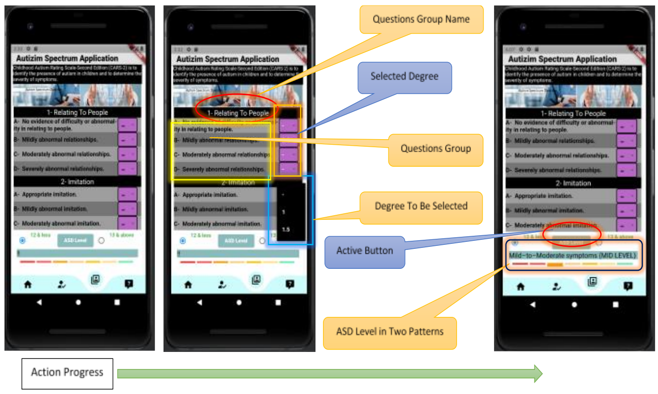

Figure 10. Steps sequence for the third interface

4. RESULTS AND DISCUSSION

The suggested mobile application for diagnosing autism and determining its severity utilizing several methods and a deep learning model needs to have its validity verified. The performance of the schemes that are used in the application is tested as part of the validation process. The testing process passes through the proposed deep-learning model in terms of training and validation, while the diagnosing and level identifying of children with autism are also considered.

With ratios of 85% and 15%, respectively, the accepted dataset is utilized to train, validate, and test the suggested deep-learning model. In this test, accuracy and loss are taken into account for both training (accuracy, loss) and validation (val_accuracy and val-loss), which are the two primary variables. The accuracy of the suggested deep learning model performance is displayed in Figure 11 for both training and validation. It is clearly shown that the results are promising well to get an accuracy of more than 97% over 40 epochs, which proves the efficiency of the model and the real ability to diagnose autistic children.

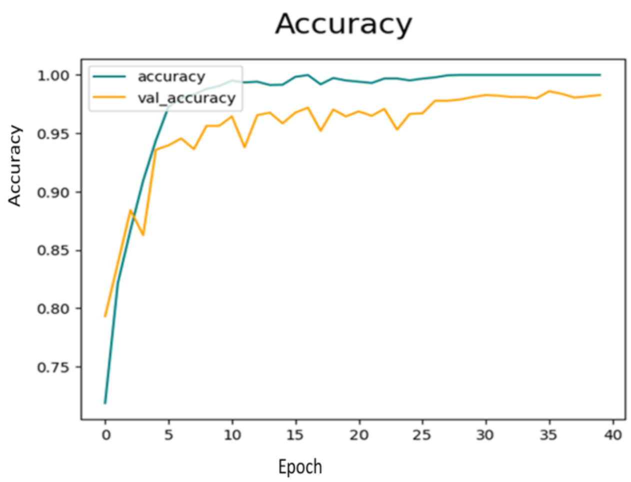

Figure 11. Accuracy in training and validation

The creator of the ML model attempts to strike a balance between two potential issues: bias and variation during the fitting step. Due to variance concerns associated with overfitting and bias problems connected to underfitting, the occurrence of these two problems diminishes with deep learning. Big data can be used to address overfitting, while deep learning architecture can handle underfitting problems. The Kaggle repository's ASD dataset is somewhat too small for deep learning to achieve good accuracy, even after excluding photographs with poor quality, wrong face positioning, partially obscured faces, tiny size, and images pertaining to various races. Because it is extremely difficult to collect new photographs from families or even from official organizations, for a variety of reasons, the augmentation activity is required to enlarge and balance the dataset. Moreover, a neural network trained on an unbalanced dataset may be too sensitive to the dominant class and disregard the minority class. By giving the minority class the proper weights or resampling methods, balancing the dataset helps to mitigate this problem by making sure the neural network gives each class equal attention and offers results based on accuracy. The aforementioned connected study did not emphasize these behaviors. Furthermore, in the event of a short dataset, it is a good idea to employ transfer learning (pre-training). However, it is also possible to achieve high accuracy by searching for specific models and focusing on certain cases.

Simultaneously, Figure 12 illustrates the suggested model's loss performance, which explains why the model performs better than others in terms of categorizing children with autism.

There are several obstacles to early diagnosis, referrals, and treatment, particularly for kids from low-income households. Lack of enough trained professionals is one of the main barriers to early identification of ASD. Another major obstacle is the variety of symptoms associated with ASD. A testing accuracy of 97.3% is attained by the suggested DL-CNN model. Our model has been tested using a reliable dataset that includes pictures of autistic and non-autistic children. It is necessary to employ a consistent method for identifying ASD that incorporates DSM-5 criteria. The term Receiver Operating Characteristic (ROC) curve refers to the graph that shows the performance of a classification model's overall categorization criteria. Plotted on this curve are two metrics: The rates of True Positive (TPR) and False Positive (FPR). The ROC curve plots for the suggested DL model, which contain the TPR vs. FPR, are displayed in Figure 13.

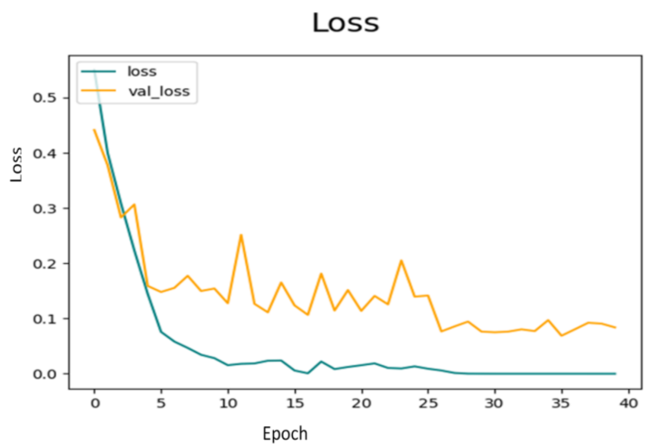

Figure 12. Training and validation loss

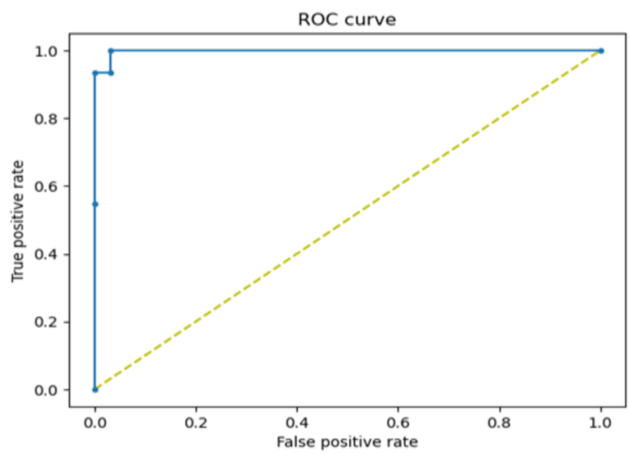

Figure 13. The suggested model's ROC curves

The area under the curve (AUC), an efficient sorting-based method, may be used to determine the points in a ROC curve. This makes sense when using integral calculus: the area under the full ROC curve in two dimensions is measured by the AUC from (0,0) to (1,1). The AUC has been recorded at 99.8%. Table 6 provides an overview of the suggested approach's accuracy and AUC ratings in relation to previous research. The findings are combined to demonstrate the recommended model's great efficiency.

Unlike traditional image classification methods, the topic of autism detection using face photographs is sensitive. The dependability and overall quality of the images used to train this model greatly influence its performance. Some of the typical visual signs of autism are wider eyes, a bigger mouth, a shorter middle face (containing cheeks and nose), a broader top face, and the philtrum (described in the introduction). Since the aforementioned traits are intimately linked to facial emotions, the only method to accurately present these facts is to provide a photograph of a face without any prejudiced expression. Excluding various races and performing augmentation improved the accuracy and quality of photographs captured by the trail runs. To ensure correct head alignment, the images must be taken against a simple, light-colored backdrop, both of the child's ears clearly visible, and their eyes wide and noticeable—that is, without any hair in the way of their vision. The suggested method is simple, efficient, and accurate, which makes it a helpful diagnostic tool for ASD. The results, which have an accuracy of 97.3% and an AUC of 99.8%, surpass the findings of previous studies published in the literature.

Table 6. Overview of the literature works

Author	Dataset	Model	Acc.	AUC
[25]	Kaggle/ ASD child	MobileNet-V1	90.7%	
[26]	Kaggle/ ASD child	MobileNet Xception InceptionV3	95% 94% 89%	
[29]	Kaggle/ ASD child	Xception VGG19 ResNet50V2 MobileNetV2 EfficientNetB0	95% 86.5% 94% 92% 85.8%	98%
[30]	Kaggle/ ASD child	VGG16	90%	
[31]	Kaggle/ ASD child	suggested	91.5%	
By Authors	Kaggle/ ASD child	The proposed	97.3%	99.8%

On the other hand, the proposed mobile application has been tested in terms of autism diagnosing using internet source 20 images: 10 ASD children and 10 non-ASD children as shown in Figure 14. The obtained results show that the accuracy is 95%, which means that just one image (image number 3) is diagnosed with error due to the wearing of eye classes.

Figure 14. Non-ASD and ASD tested images

The proposed mobile application is tested in a case study of a child with autism, where the deep-learning model is diagnosed as autistic, as shown in the first interface of Figure 15. The diagnosed child is passed to the identifying the autism level with the DSM-5 method that second level (B), which is mild autism, as illustrated in the second interface of Figure 15. Moreover, The CAR-2 method is tested by applying the autistic child to the related application part. The obtained result identifies the child with a severe level of autism, as explained in the third interface of Figure 15. The slide difference between the DSM-5 and CAR-2 methods is due to the diversity of questions in CAR-2 and the flexibility of choosing the right answers by parents or alternatives.

Figure 15. Mobile app performance over a case study

The suggested mobile application's usability and simplicity were assessed, and the findings point to favorable ratios. To complete the test, three groups were presented, each with a sample size of 100. The first category consists of non-experts, who lack knowledge of ASD symptoms and behaviors. The second was the person who raised and cared for an autistic child. The final set of people had a thorough grasp of ASD; they were doctors and assistants who worked in or around the subject. The user feedback ratio is shown in Table 7.

Table 7. Mobile application usability feedback

Sample Type	Sample Number	Average
Non-Expert	100	78%
Have Autistic child	100	89%
Experts	100	96%

5. CONCLUSION

Many factors played a role in the decision to select the facial image method for diagnosing ASD over other approaches such as question lists with screening, MRI imaging, and eye tracking. Family time and expenses are tied to elements like cognitive and language exams, behavior observation, patient interviews, and other. A smartphone application was created to assist families in identifying their children if they are ordinarily developing or suffering from autistic conditions (ASD) according to the DL model classifier that was constructed utilizing face photos. The DL model was trained, validated, and tested using a suitable number of images representing both typically developing and ASD children. Results showed that the DL model could diagnose patients with high accuracy rates, with an AUC of 99.8% and an accuracy rate of 97.3%. Based on children's still-face images, these results showed that it was feasible to accurately identify the defining traits of ASD, opening the door to a rapid and precise ASD screening process. Furthermore, the DSM-5 and CAR-2 methods of determining an individual's autism level are included in the planned mobile application, which is a crucial step. By using the suggested application, caregivers properly determine their child's ASD level, which will aid them in combating this disease by guiding them to follow the standard educational support specified for each level. A case study demonstrating well-executed techniques confirmed the validity of the level-identifying exam. For the two caregivers and the ASD children, the mobile application can include additional scales, other testing scenarios, visual assistance, learning support, improving skills, etc.

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