Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 14, Issue. 2, No. 1: 2023
ISSN : **1906-9685**

DEEP LEARNING ALGORITHMS FOR CHILDREN-BASED FACIAL EXPRESSION TO RECOGNIZE AUTISM SPECTRUM DISORDER

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Abstract
People with autistic spectrum disorders (ASDs) have difficulty recognizing and engaging with others. The symptoms of ASD may occur in a wide range of situations. There are numerous different types of functions for people with an ASD. Although it may be possible to reduce the symptoms of ASD and enhance the quality of life with appropriate treatment and support, there is no cure. Developing expert systems for identifying ASD based on the facial landmarks of children is the main contribution for improvements in the healthcare system in Saudi Arabia for detecting ASD at an early stage. However, deep learning algorithms have provided outstanding performances in a variety of pattern-recognition studies. The use of techniques based on convolutional neural networks (CNNs) has been proposed by several scholars to use in investigations of ASD. At present, there is no diagnostic test available for ASD, making this diagnosis challenging. Clinicians focus on a patient's behavior and developmental history. Therefore, using the facial landmarks of children has become very important for detecting ASDs as the face is thought to be a reflection of the brain; it has the potential to be used as a diagnostic biomarker, in addition to being an easy-to-use and practical tool for the early detection of ASDs. This study uses a variety of transfer learning approaches observed in deep CNNs to recognize autistic children based on facial landmark detection

Keywords-Autism Spectrum Disorder (ASD), E-Learning System, Data Mining, Classification techniques, facial appearance

1. Introduction

More than one billion people on the earth live with some form of impairment, and over 150 million school-age children worldwide are certified to have some form of disability. Many of these kids don't complete their necessary training and are turned away from educational chances. In a similar vein, a recent UNESCO Global research reveals that people with disabilities face a wide range of obstacles, such as lack of employment opportunities and access to information and education. Information and communication technologies (ICT) can, however, be a useful tool in assisting with training and taking into account the needs of those who are disabled. Advancements in technology have the potential to enable people with disabilities to improve their level of personal satisfaction. By utilizing these technologies effectively, learning environments may become more accessible, systems can become more responsive to the requirements of students, and classrooms can become more complete.

To be honest, the constant advancement of ICT made it necessary to strive toward improving the quality of learning associated with education and creating frameworks by taking into account fresh perspectives and opportunities. E- learning emerges as a means of meeting that demand [1] and promises to provide a comprehensive and customized approach to meeting the understudies' changing needs. It's true that there is promise for e- Learning's potential to lessen obstacles to training and improve the lives of those with disabilities [2].

As a result, developing accessible online learning environments appears to be a crucial solution for addressing this problem and removing any obstacles that people with disabilities might encounter when using these learning technologies. A suitable innovation should provide people with disabilities with personalized, adaptive learning experiences that are tailored to their unique learning styles and educational requirements. Additionally, it should improve their learning effectiveness, speed, and enjoyment.

2. Background of Study

Extreme wrapping of impedances in a few key areas of a man's improvement is what utism entails [13]. Any of the accompanying cases—behavioral, imaginative, social interactions, and communication—could pose these obstacles [14]. Even though some autistic children may have been raised with typical knowledge, the majority of autistic children struggle with learning [15]. These children's disabilities may also be categorized as being related to epilepsy, vision, or hearing problems. Autism is linked to a man's behavior and is thought to be caused by unknown biological mental dysfunctions that affect how the brain responds to stimuli and develops while handling information. This brokenness can include problems with any of the processed or even decoded data.

Children with autism typically suffer from negative behavior, poor social interaction, poor communication, and significant differences in their learning capacities. Zander (2004) [16] posited in the article "Introduction to Autism" that social collaboration is the main problem faced by mentally unbalanced children. These children struggle with directing eye contact, nonverbal communication, outward appearance, and modulation. Many children with autism don't show social or intense criticism, and they also don't show their emotions to other people [17]. Additionally, it has been observed that children with autism lack the same interests as other children their age.

Even if they could, they are unable to effectively communicate, establish, and manage fellowships. Children with autism actually experience delayed language development. The result is that many of these autistic children develop poor speaking skills since it can be challenging to help autistic children develop their social and relational skills [16]. In addition, they exhibit unusually perceptive behavior that includes restrained curiosity and concern about a specific issue, strict adherence, and flexible recognition of non-utilitarian consistency. [16] also outlined instances of these recognition behaviors, such as spinning a toy's wheel, arranging toys in a monotonous manner, but infrequently drawing themselves in abruptly and obtaining unique diversion and pretends.

In addition to this, [16] further reasoned that, in terms of knowledge and learning capacity, the severity of autism in children varies from person to person. This could be due to a number of factors, such as depression, the nature of the autism condition, epilepsy, inherited signs, and so forth. As a result, it becomes necessary to develop a successful and efficient teaching method for these children. A few effective teaching techniques have been identified for use with these autistic children.

3. Proposed System:

The aim of this study was to investigate if children exhibit early indications of autism spectrum disorders (ASD) using a transfer learning person equipped with machine learning algorithms for autistic facial appearances and landmark detection. In this study, children's facial landmark features were automatically extracted to identify ASD using a combination of deep learning and machine learning techniques. Because of their complexity, these traits are extremely difficult, if not impossible, to discern by eye. After that, we put these traits through a sequence of layers, with the topmost, densest layer yielding the diagnosis of ASD. The ASD diagnosis system's framework is depicted in Figure 1.

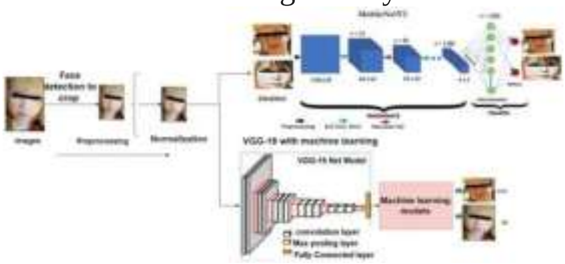

Figure 1. Framework of the proposed recognition system

3.1 Dataset

This study made use of facial image data from the autistic children's Kaggle dataset. We created the models we presented using this dataset since it is the only one of its sort that is available to the public. The sample comprised children ages 2 to 14 years, the majority of whom were in the 2 to 8 age range. The images were all 2D RGB jpegs. There were two classes in the dataset: pictures of kids with autism were in the autistic class, while pictures of kids without autism diagnoses were in the non-autistic class. The images needed to test the model after it was trained were contained in a test folder. There were one hundred 224 × 224
× 3 jpeg photos in each subdirectory. The faces of children with autism were gathered at random via

internet searches and placed in the autistic subfolder, whereas the non- autistic subfolder included the faces of children without autism. There were 2940 photos in the dataset, 1327 of which featured children with autism and 1613 of which did not. Figure 2 displays a dataset sample.

Figure 2. Images of autistic and non- autistic children.

3.2. Deep Learning Models

Neural networks, which have been demonstrated to be useful in the categorization and detection of ASDs, are burdened by CNNs. ConvNets have names derived from the veiled layers they include, which may be why they resemble inscriptions. Three components make up a CNN: pooling, convolution, and a fully linked layer [6]. Local picture properties are gathered via convolution, dimensionality is decreased through pooling, and the required output is produced by the fully connected layer. Brighter pixels are used to show the boundaries of the image in this mode, which emphasizes local visual details. Better processing is also possible [43, 44].

Each of the network's basic layers contains an activation function in addition to convolution and pooling functions. The same image that is fed into the convolution process coupled with one filter is the output. Numerous aspects impact the neural network's performance, such as the image size (224 × 224 × 3), height, width, and channels. The processing size of the image channel was 49,152 bytes, with a height of 200 by 200 pixels. The RGB color model (224 × 224 × 3) was employed by the image channel. For example, if the image has three dimensions of 2048 by 2048, then a weighted extent size of 12 million is needed.

C = ∑ i 1 ∑ j 1 IijFij (1)

The letter F stands for a convolution kernel or filter, and the letters i and j stand for rows and columns. For example, Figure 3 shows the raw image and filter after the image has been multiplied by the kernel. The newly created output value is shown in Figure 4. Two-dimensional arrangement. The convolution process divides the image into perceptrons. They are then successively planed along the (y), (x), and (z) axes. Every stratum has a number. Various filters that can be applied to find specific characteristics. The addition of the following annotations to the feature maps of X sizes generated by layer L:

C L i = B L i + ∑ x (L−1) j=1 F L i,j ∗C (L−1) (2) where B L i : bias matrix. F L i,j : filter linking jth based on the feature map in the layers.

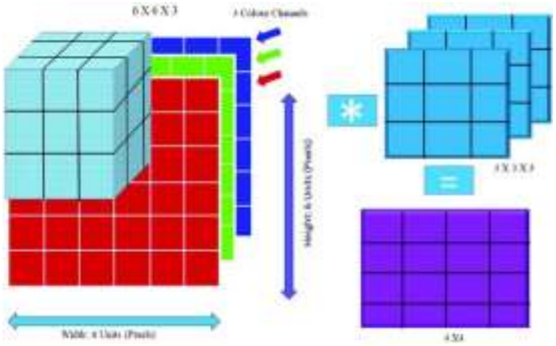

Figure 3: Filter matrix of the convolution operation

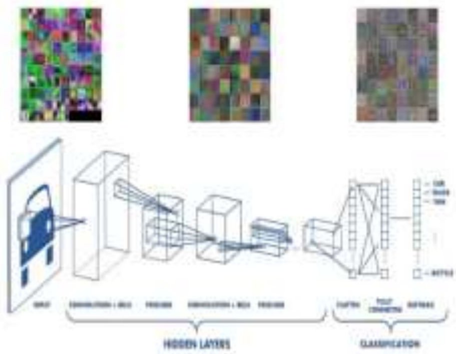

Figure 4: Convolution neural network

For example, the blue channel may have a value of −1, whereas the other channels might have values of +1 or 0. Utilize the dot product in order to calculate the value of the convolution. Convolution is a process that warps images. In this demonstration, (Is) equals 1. If both (Is) and (Is) are true, then (Fs) (Fs) describes the same image size (Fs).

$Cs = ((Is - Fs)/S) + 1$ (3)

If the values of Is, Fs, and S are 6, 3, and 1, respectively, then $Cs = (6 - 3 + 1) = 4$. The following is how the output dimension was calculated:

$(Width - Fs + 2P)/S] + 1c$ (4)

where Fs is the filter size, padding is P, S is stride, and Equation (4) is the floor value.

3.2.1. MobileNet Architecture

A deep learning model called MobileNet was created to efficiently classify images on many technology platforms, including low- power PCs without a GPU, embedded systems, and mobile devices [38]. The fundamental architectural structure of the MobileNet model is shown visually in Figure 5. One essential component that sets. The feature that sets this CNN model unique from others is the depth-wise separable filters, which carry out convolutions both point-wise and depth- wise.

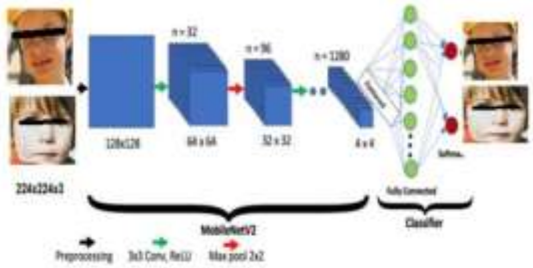

Figure 5: MobileNet's structure

In contrast to conventional convolution methods, depth-wise convolution uses a range of filtering approaches to extract feature maps by utilizing each channel of the input image independently. When the output image's number of channels is increased to the appropriate number, employing filter masks with sizes of (1 1) leads to a notable decrease in the duration of the amount of time the computer needs to process. This type is widely recognized as an easy-to-use deep neural system. There are numerous uses for MobileNet, some of which comprise face feature recognition, object detection, fine-grain classification, and geographical placement.

3.2.2. Hybrid VGG-16 with Machine Learning Models

The VGG-16 model is a pre-trained image recognition model developed by the Visual Geometry Group (VGG) at the University of Oxford.The ImageNet dataset, a sizable collection of images, was used to train this model.More than 1000 different categories and over 14 million photos make up this dataset. In order for the model to recognize and classify objects in the images it is shown, it must first identify properties from the image itself during the training phase. As the network's size is expanded, the deep neural network's correct operation may be verified.

The VGG was responsible for building networks A, A-LRN, B, C, D, and E. All VGG networks have ReLu; however, they do not really use it since executing local response normalization takes more time and memory space during training [10]. The most significant difference between AlexNet and VGG is that AlexNet has an 11
× 11 kernel with a stride of 4 × 4, whereas VGG uses a 3 × 3 kernel with a stride of 1
× 1. The 1 × 1 convolution filter that VGG provides is useful for both predictive modeling and classification work

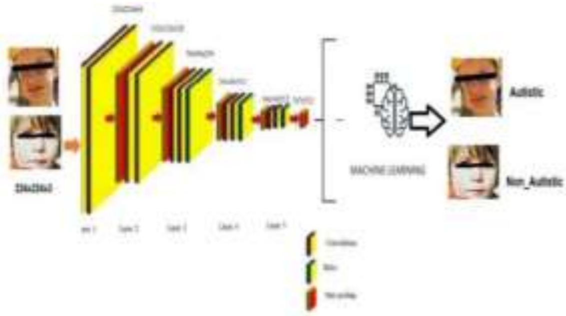

Figure 5: VGG-16 structure

3.3. Measuring the ASD Diagnosis System's Performance

To assess the efficacy of the provided algorithms in detecting ASDs, the evaluation metrics included sensitivity, specificity, precision, and recall scores, as well as the F1-score.

4. Experiments, Result & Discussion

The training of the MobileNet learning models with the assistance of the Keras API Library was applied. Matplotlib, Sklearn, and Pandas are just a few examples of the data visualization and analysis tools utilized in the process of determining the effectiveness of the models. We used a standard set of hyperparameters with the following values to compare the performance of MobileNet-based models trained with different optimizers with a batch size of 80 and a learning rate of 0.001 across 100 epochs. The dataset comprised a total of 2940 images, of which 2540 were
utilized for training, 300 were utilized for testing, and 100 were utilized for validation. As can be observed in Table 2, when we were building the data frame, we provided an image a value of 0 for children in the normal control (NC) group and a value of 1 for children who were diagnosed with ASD. It is observed that the MobileNet model achieved an accuracy of 92%

Table 1. Results of MobileNet model

	Precision %	**Recall %**	**F1-Score %**	**Support**
Autism	83	81	82	291
Normal	82	83	82	297
Accuracy		82.14		
Macro avg	82	82	82	588
Weighted avg	82	82	82	5888

The paper presents the outcomes of the hybridization of the VGG-16 deep learning model with several machine learning models, such as logistic regression, Linear SVC, random forest, decision tree, gradient boosting, MLPClassifier, AdaBoost, and K- nearest neighbors. We used the VGG-16 model without its upper layers in this investigation. This indicates that not all of the layers in the model are completely connected to one another. This made it easier for the model to extract the features from the photos, and the process ended with a "feature map" that contained those features. The input shape of the model was given the 224 224 3 dimensions that are typical for a VGG-16 model.

Table 2. Results of VGG-16 with logistic regression

	Precision %	Recall %	F1-Score %	Support
Autism	92	92	92	150
Normal	92	92	92	150
Accuracy		92		300
Macro avg	92	92	92	300
Weighted avg	92	92	92	300
Overall results	90.47	92	92	

5. Conclusion

Facial landmarks hold potential as an autism spectrum disorder (ASD) screening tool. Developing a clear and educational paradigm for ASD diagnosis is essential to overcoming the difficulties associated with working with children. Because of the complexity of attentional behavior in people with ASDs, creating such systems is a difficult endeavor. For people seeking treatment for ASDs, the best results come from early diagnosis and management. In the past, diagnosing ASD in children has required hospitalization; this is a costly and time-consuming procedure that is also prone to expert bias [45]. In this paper, we established an objective, practical, and useful method for using facial expressions to diagnose children with ASD.

Our results reveal that the proposed model achieved an accuracy of 92%. The accuracy of MobileNet's results was evaluated using the ROC metric, with true-positives for normal and pathological classes presented on the y-axis and false-positives indicated on the x-axis. The results of the MobileNet model compared to different existing systems .

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