

Transfer Learning Approach for Detection of Autism Spectrum Disorder using Facial Images

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Abstract—Autism Spectrum Disorder (ASD) is characterized by deficits in social interaction, communication issues, and repetitive behavioral patterns. Effective ASD intervention and assistance depend on early detection and diagnosis. Children with autism differ noticeably from normally developing (TD) children in their patterns of facial features. Autism may be indicated by a child's eyes, nose, and lip distances as well as their placement. Using common evaluation measures like accuracy, sensitivity, and specificity, the built ASD detection system is assessed. The outcomes of this study show the utility of facial image analysis in the identification of ASDs. The proposed strategy shows potential in aiding physicians and researchers in early diagnosis by utilizing face clues and machine learning techniques. This study aims to investigate how well machine learning and feature extraction algorithms based on deep learning can identify ASD in young children. Deep convolutional neural networks known for their capacity to extract significant characteristics from images, VGG16 and VGG19, are used. Several machine learning algorithms, such as logistic regression, support vector machines (SVM), naive Bayes, and artificial neural networks (ANN), are then applied with the retrieved characteristics as input.

Index Terms—Autism, Deep Learning, Machine Learning, VGG16, medical feature extractions, Facial Images

I. INTRODUCTION

Autism spectrum disorder (ASD) a range of complicated neurodevelopmental diseases that impact speech and behavior and are brought on by variations in the brain. People with ASD have ongoing difficulties with social communication, the ability to form, sustain, and comprehend relationships, as well as repetitive and constrained patterns of behavior. Autism is seen as a spectrum disorder because each autistic person experiences it differently. Some autistic people may require more care than others to live their desired lifestyles. The wide variety of symptoms linked to ASD make diagnosis difficult [1]. Studies have demonstrated that early identification and treatment can enhance a person's long-term prognosis despite the fact that ASD is a chronic disorder. Medical interventions are used to treat this illness, although there is little proof that

most of them are effective. These intervention techniques should be used to establish an accurate diagnosis of ASD as soon as feasible. The inability to find a single medical test that can reliably identify ASD makes diagnosis difficult. Before a kid turns one year old, parents, carers, or pediatricians can spot the first symptoms of this illness. However, symptoms typically begin to manifest more consistently in children when they reach the age of 2 or 3. The autism spectrum disorder was diagnosed one of the other options is to use neuroimaging data from relatively expensive methods [3]. This study aims to investigate how well machine learning and feature extraction algorithms based on deep learning can identify ASD in young children. The deep convolutional neural network VGG16 and VGG19 models, which are renowned for their capacity to extract significant characteristics from images, are used. Various machine learning algorithms, such as logistic regression, support vector machines (SVM), Naive Bayes and artificial neural networks (ANN), are then applied with the retrieved characteristics as input. Additionally, methods like grid search are used to enhance the performance of machine learning models by optimizing their hyperparameters. The results of this study have the potential to have a substantial influence on the diagnosis of ASDs by offering a non-invasive, scalable method for early detection. This might result in prompt support and interventions for kids with ASD, enhancing their general quality of life. The rest of the paper has the following structure: The section provides in depth analyses of prior research and studies in the area. The approach used is explained in depth in Section 3 along with the dataset used, preprocessing procedures, feature extraction using VGG16 and VGG19, machine learning algorithms used, and evaluation techniques. Section 4 summarizes the findings and reviews how each model performed. The results are shown in Section 5 along with a discussion of them. The work is concluded in Section 6, which also identifies potential directions for further investigation.

II. LITERATURE REVIEW

Using face pictures, researchers have employed a number of methods to identify whether or not a subject has autism. The numerous studies that were carried out to establish if a person was autistic are this section's main topic. Using MobileNet and two thick layers, the deep learning model proposed by Beary et al. for 2020 performs feature extraction and image categorization. 3,014 images, equally divided between children who are autistic and who are not, are used for training and testing the model. 90% of the data is used for training, and 10% is used for testing. [1]. While Banire et al. 2021 proposed a model based on two separate methods for identifying facial attention. While the first applied a support vector machine (SVM) classifier to interpret geometric knowledge of the faces of children, the second used a convolutional neural network (CNN) technique to transform time-domain spatial attributes into 2D spatial images. In this experimental study, the researchers examined the limitations of the model which recognized face-based attention, for each individual and task differences utilizing a variety of attentional tasks for 46 children (20 having ASD, 26 normally growing). [2]. The research work by Tamilarasi et al. from 2020 investigates if specific facial features, such as the spacing between a child's eyes, nose, and lips, and how they are placed, can operate as markers of autism. These sites were categorized using a variety of classifiers, including SVM, KNN, and Naive Bayes. They looked at various methods and techniques for computing contour extraction, such as using a clip-limited adaptive algorithm to determine area and perimeter. The feature extraction technique includes analysing the face's texture. [3]. The model proposed by Sadik et al. in 2021 was implemented using Convolutional Neural Network (CNN) technology. In order to increase the model's efficacy, the transfer learning technique was also used in this work. The experimental results validated the transfer learning approach of the MobileNet model. The F1-score and accuracy value further confirmed the technique's dependability. [4]. In their study Michelassi et al in 2021. investigate a computer-aided healthcare decision-making system. Based on a digital camera photograph of a child's face, it can tell the difference between ASD and TD. The diagnosis may benefit from this. They developed an approach for acquiring and processing images, tried out, and assessed several dataset balancing, dimension reduction, and classification methods. The best results were achieved with the SVM classifier. [5]. According to Rahman et al. 2022, a research study was conducted to investigate if there were any static characteristics in autistic children's faces that could possibly be used as a biological marker to differentiate them from normally developing children. To accurately detect autism in young children, they used a DNN model with five pre-trained CNN models [6]. Classification models utilizing the OpenCVier VGG16, SVM, CNN, and Haar Cascade are the main subject of the work by Ganesan et al. 2021 [7]. The core idea of Elbattah et al. 2022 is to convert eye-tracking scan routes into a visual representation, potentially making it easier to use trained vision models. Popular models including VGG-16, ResNet, and DenseNet

were used in the studies. The outcomes demonstrate that the Transfer Learning method is capable of accurately classifying data at an impressive rate (ROC-AUC up to 0.78). [8]. In their research, Saranya et al. 2022 empirically link facial emotions to ASD using the Facial Action Coding Systems (FACS), which extracting the various features. DEEPFACENET combines the FACSembed- ded convolutional neural network (FACS-CNN) and hybrid deep learning of LSTM for feature extraction in order to categorize and daignose autism spectrum disorders (ASD). [9]. The study by Ahmed et al. 2022 intended to provide families and psychiatrists with a simple way to the autism diagnosis. Models for classifying data before were MobileNet, Xception, and InceptionV3.They developed a deep learning- based web application for autism detection based on facial features that have been verified by experimentation, integrating a convolutional neural network with transfer learning and a Flask framework. [10].

III. METHODOLOGY

- A. **Data Description:** The present study analyzed the visual traits of autistic and normal children using images from the publicly accessible online Kaggle platform. The dataset comprised 2,940 face images, of which half were of children with autism and the other half were not. The images were then split into 2,540 training images, 100 validation images, and 300 testing images.
- B. **Data Pre-processing:** As a part of data pre-processing normalization and data augmentation was carried out. The normalization approach was used to scale images of the dataset. All the image parameters were normalized. The images were augmented by rotating them horizontally and vertically.
 1. **Normalization:** Normalization is a common preprocessing technique used to scale images before feeding them into machine learning models or performing computer vision tasks. It makes sure that an image's pixel values are translated into a uniform range, usually between 0 and 1. Normalization helps to bring consistency and numerical stability to the data, making it easier for the model to learn patterns and improve convergence during training.
 2. **Augmentation:** A popular method for expanding the dataset's size and diversity is image augmentation. Image augmentation enhances the generalisation and robustness of the analysis or model training by applying numerous alterations to the already-existing images. The common image augmentation techniques are Rotation, Scaling, Flipping, Cropping, etc.
- C. **Feature Extraction:** To classify individuals as either having autism or not, we utilized pre-trained machine learning models, namely VGG16 and VGG19, as feature extractors. These models have the capability to automatically extract robust features, which are often

subtle and challenging to identify through basic observation alone. This enables us to perform accurate categorization with a high level of precision. Feature extraction refers to the process of identifying and extracting meaningful visual characteristics or patterns from the images that are relevant for facial analysis or recognition tasks. These features capture the

distinguishing characteristics of a face, such as the arrangement of facial landmarks, the texture, and the colour information. Feature extraction in facial images is typically performed using computer vision techniques or deep learning models. The objective is to convert an image's original pixel values into a set of numerical characteristics.

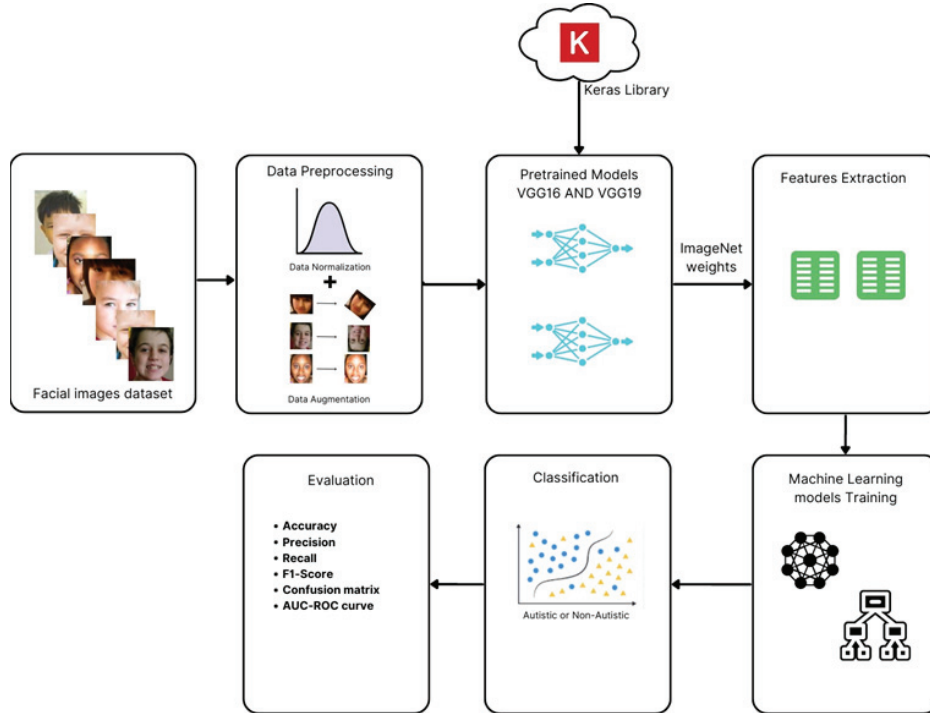


Figure 1: Proposed Model

D. Feature Extraction Models:

1. **VGG16:** The VGG16 architecture was initially introduced by the Visual Geometry Group (VGG) at the University of Oxford. It emerged as a strong contender in the 2014 ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) competition and demonstrated remarkable performance, highlighting the effectiveness of deep learning in image classification tasks. The name "VGG16" is derived from two components: "VGG," representing the Visual Geometry Group, and "16," which signifies the total number of layers present in the network. The main features of VGG16 are its consistency and simplicity in architecture, which make it simple to comprehend and use. The network accepts a 224x224 pixel image as input. VGG16 has 13 convolutional layers, each of which is followed by a 3x3 filter with a stride of one and a ReLU activation function. From 64 to 512 filters are added one at a time. VGG16 uses max pooling with a 2x2 window and a stride of 2 to decrease the spatial dimensions of the feature maps after every two convolutional layers. Each of the 4096 neurons in the three fully connected layers of

VGG16 is followed by a ReLU activation function. A softmax layer with the same number of neurons as classes in the classification task makes up the final layer. To learn general features from millions of photos, the VGG16 model is generally pre-trained on largescale image datasets like ImageNet. The pre-trained weights are capable of capturing rich representations, which may then be transferred and modified for a range of computer vision tasks such as image segmentation, object recognition, and image classification. VGG16 can be used as a powerful feature extractor by utilizing its convolutional layers. By removing the fully connected layers and keeping only the convolutional layers, we can leverage the learned representations from VGG16 for various computer vision tasks such as feature extraction, transfer learning, and image representation.

2. **VGG19:** The Visual Geometry Group (VGG) of the University of Oxford created the VGG19 architecture, which is an expansion of VGG16. VGG19 shares many similarities with VGG16 but has a deeper architecture with 19 layers, hence the name "VGG19". The key characteristics of the

VGG19 architecture are similar to VGG16, but with additional convolutional layers to increase the depth of the network. Takes a 224x224 pixel image as input. Each of the 16 convolutional layers in VGG19 is followed by a 3x3 filter with a stride of 1 and a ReLU activation function. The number of filters gradually increases from 64 to 512. After every two convolutional layers, the spatial dimensions of the feature maps are condensed using max pooling with a 2x2 window and a stride of 2. Following a ReLU activation function, VGG19 has three fully connected layers with a total of 4096 neurons each. A softmax layer with the same number of neurons as classes in the classification task makes up the final layer. VGG19 is a deeper and more powerful variant of the VGG architecture, capable of capturing more complex image features. VGG19 can also be used as a feature extractor by leveraging its convolutional layers. Similar to VGG16, we can remove the fully connected layers and utilize the convolutional layers to extract meaningful features from images.

E. Data Division: In order to implement the suggested approach, the images were divided into three distinct sets: the training set, the validation set, and the test set. These sets serve the purpose of training, validating, and evaluating the models, respectively. The effectiveness of the model is assessed by analyzing the results obtained from the test set. Before constructing the model, it is imperative to train and validate it using specific sets of images designated for training and validation purposes. The model's performance is then evaluated using a different set of newer images, referred to as the test images. Images that are labeled with the words "autistic" or "non-autistic" are included in the training and validation sets. Consequently, a machine learning model for ASD screening that has been properly trained can classify a child based purely on a face image. Each model was first trained using a training set of 2540 photos (in two classes), and its performance was then verified using a validation set of 100 photos (in two classes). 300 test photos were utilised to assess the predictor's performance.

F. Classifier Module: The several thousand features acquired by the feature extractor modules were used to classify the person as having autism or not using machine learning and deep learning models. Therefore, to classify a person as autistic or not, we utilized Logistic Regression, Naive Bayes, Support Vector Machine, Random Forest, Gradient Boosting Classifier and Artificial Neural Network.

G. Models:

1. **Logistic Regression:** Logistic regression is a statistical approach that predicts a dependent variable that is categorical using one or more variables that

are independent. It is a specific kind of generalized linear model where the dependent variable is assumed to have a binomial distribution, where it takes on one of two possible outcomes. By applying a logistic function to the data, the model estimates the probability that the dependent variable will have a specific value given the values of the independent variables.

$$\ln \frac{\hat{p}}{(1 - \hat{p})} = b_0 + b_1x_1 + b_2x_2 + \dots + b_px_p \quad (1)$$

Here X is the independent variable(s), $b_0, b_1, b_2, \dots, b_p$ are the coefficient(s) on the independent variable(s) and \hat{p} estimated probability of the dependent variable taking on a specific value.

2. **Naive Bayes:** The approach is based on Bayes theorem, which quantifies a hypothesis likelihood given the available data. In the case of Naive Bayes, the presence or absence of one characteristic has no effect on the likelihood of any other feature. In order to determine each class' likelihood in the absence of any feature information, Naive Bayes first determines each class' prior probability based on the training data. The likelihood of an event A given an event B differs from the likelihood of an event B given an event A as in equation during a Bayesian analysis.

$$P(A|B) \quad P(B|A) \quad (2)$$

Assuming that A_1, A_2, \dots, A_n are the feature vectors and C is the class of the water quality, respectively, the Bayes equation can be expressed as follows:

$$P(C|A) = \frac{P(C) \times P(A|C)}{P(A)} \quad (3)$$

where the $P(A|C)$ is a prior probability of the class of the water quality and $P(A)$ is the prior probability representing the feature vectors of the Water quality.

3. **Support Vector Machine:** Machine learning algorithm used for both classification and regression tasks. It works by finding the hyperplane that best separates the data into different classes or predicts the continuous target variable. In binary classification, the hyperplane is the line that separates the data into two classes, while in multiclass classification, it is a hyperplane in higher-dimensional space that separates the data into multiple classes. The SVM algorithm tries to find the hyperplane with the maximum margin, which is the distance between the hyperplane and the closest data points from each class. This maximizes the separation between the

classes and reduces the risk of overfitting. If the data is not linearly separable, SVM uses a technique called kernel trick, which maps the data to a higher-dimensional feature space, where it is more likely to be linearly separable. This allows SVM to capture complex non-linear relationships between the input features and the target variable.

4. **Random Forest:** It uses machine learning to create a tree-like model of choices and results, with each internal node denoting a test on an attribute or feature and each leaf node suggesting a class label or numerical result. When splitting the data at each internal node, the algorithm first separates the feature space into informative features and then selects the most suitable attribute or feature. The algorithm used to build a decision tree chooses the best feature to divide the data at each node. This decision is made using a metric for impurity reduction or information gain. Information gain quantifies the reduction in entropy, while impurity reduction can be assessed using metrics such as the Gini index or misclassification rate.

Based on the values of the selected feature, the decision tree method splits the dataset into subgroups. This process is iteratively repeated on each subset until a specific stopping requirement is satisfied, which could be reaching a maximum depth or having a minimal amount of samples per leaf.

Although they are prone to overfitting, decision trees can deal with both categorical and continuous data.

5. **Gradient Boosting Classifier:** Gradient Boosting Classifier is a machine learning algorithm that uses the ensemble method and combines various individual models to enhance performance. It is based on decision trees and is used for classifying challenges. Gradient Boosting Classifier produces a series of decision trees, each of which attempts to correct the faults introduced by the previous tree. The method starts the training phase by constructing a single decision tree and making predictions based on the training data. The difference between the expected and actual values is then computed, and a new decision tree is trained to forecast the difference. This process is repeated several times, with each new tree adding to the overall prediction and predicting the flaws of the previous tree. The approach uses the gradient descent method to reduce the loss function. By continually altering model parameters in the opposite direction of the loss function's negative gradient, gradient descent minimises error.
6. **Artificial Neural Network (ANN):** ANNs are highly versatile and can be employed for various applications, including classification, regression, pattern recognition, and more. An artificial neural

network consists of interconnected nodes, commonly known as neurons or units. These neurons are organized into different layers within the network. During training, the neural network adjusts the weights associated with the connections between neurons in different layers. The objective of this adjustment is to enable the network to learn and recognize patterns and relationships within the given data. To minimize the discrepancy between the network's predictions and the actual targets, the weights in the network are iteratively adjusted using optimization techniques such as gradient descent. The neural network can simulate complicated relationships in the data with the help of activation functions, which are utilised to incorporate nonlinearities into the network.

- H. **Evaluation:** The accuracy, precision, recall, F1 score, and support matrices were among those utilized to evaluate the deep learning and machine learning models. The performance of the models is shown visually by the confusion matrix. Accuracy: Accuracy is an evaluation statistic that shows the proportion of the model's true predictions to all of its other predictions. It is possible to represent accuracy using equation (5).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (3)$$

Precision: Precision is determined by dividing the total number of positively classified samples by the proportion of correctly classified Positive samples that belong to the Positive class. Equation (6) provides a mathematical description of precision.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

Recall: Recall is defined as the proportion of Positive samples in the positive class that were correctly classified to all of the Positive samples. The mathematical equation of Recall is described in Equation (7)

$$\text{Recall} = \frac{\text{TP}}{\text{TN} + \text{FP}} \quad (5)$$

F1-Score: The harmonic mean of recall and precision is the F1 score. Instead of looking at a model's overall performance like accuracy does, it elaborates on how well it performs in each class. Equation (8) can be used to represent it

$$\text{Precision} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

where True Positive (TP) is a patient with an autism spectrum disorder (ASD), False Positive (FP) is a healthy person with an ASD, True Negative (TN) is a healthy person with an ASD, and False Negative (FN) is an ASD patient with an ASD.

IV. RESULTS AND DISCUSSION

The goal of this project is to provide an effective method for identifying ASD in young children utilizing facial image analysis and deep learning techniques. VGG16 and VGG19 models for feature extraction from facial pictures are transfer learning models that can be used to accomplish this. The retrieved features were then classified to ascertain the existence of ASD using a variety of machine learning algorithms. Using VGG16 and VGG19 for feature extraction, the accuracy, precision, recall, F1-score, and confusion matrix of various machine learning models were assessed. The performance ratings of the models on the characteristics that were retrieved using the VGG16 model are listed in Table 1. In both the VGG16 and VGG19 feature extraction models, Support Vector Machine with hyperparameter tuning and Artificial Neural Network outperformed the other models, earning the highest accuracy rates of 81.41% and 80%, respectively. These findings suggest that the SVM-based

models were successful in correctly categorising ASD-affected kids using facial image characteristics derived by VGG16. Naive Bayes achieved an accuracy of 72%, suggesting relatively lower performance compared to the SVM models. The accuracy ranged from 71% to 78% for Logistic Regression, Naive Bayes, Random Forest Classifier, Gradient Boosting Classifier, and Artificial Neural Network based on VGG16 features. These models performed rather well in identifying ASDs, however the SVM-based models somewhat outperformed them. The outcomes for the VGG19 model were in line with those of the VGG16 model. While SVM obtained an accuracy of 78%, SVM with GridSearch reached an accuracy of 80%. Accuracy rates for Naive Bayes and Logistic Regression were 71% and 78%, respectively. The same pattern were observed for VGG19 as feature extractor. Figure 2. and Figure 3. illustrate the confusion matrices of the top 3 best performing models on features extracted using VGG16 and VGG19 respectively.

TABLE I: PERFORMANCE ANALYSIS OF MODELS FOR VGG16

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	0.81	0.80	0.83	0.82
Artificial Neural Network	0.80	0.80	0.79	0.80
Logistic Regression	0.79	0.79	0.79	0.79
Gradient Boost Classifier	0.77	0.77	0.77	0.77
Random Forest Classifier	0.75	0.75	0.77	0.76
Naive Bayes	0.72	0.73	0.69	0.71

TABLE II: PERFORMANCE ANALYSIS OF MODELS FOR VGG19

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	0.80	0.8	0.79	0.80
Artificial Neural Network	0.80	0.80	0.79	0.80
Logistic Regression	0.78	0.77	0.79	0.78
Gradient Boost Classifier	0.78	0.77	0.80	0.78
Random Forest Classifier	0.76	0.75	0.78	0.76
Naive Bayes	0.71	0.72	0.69	0.70

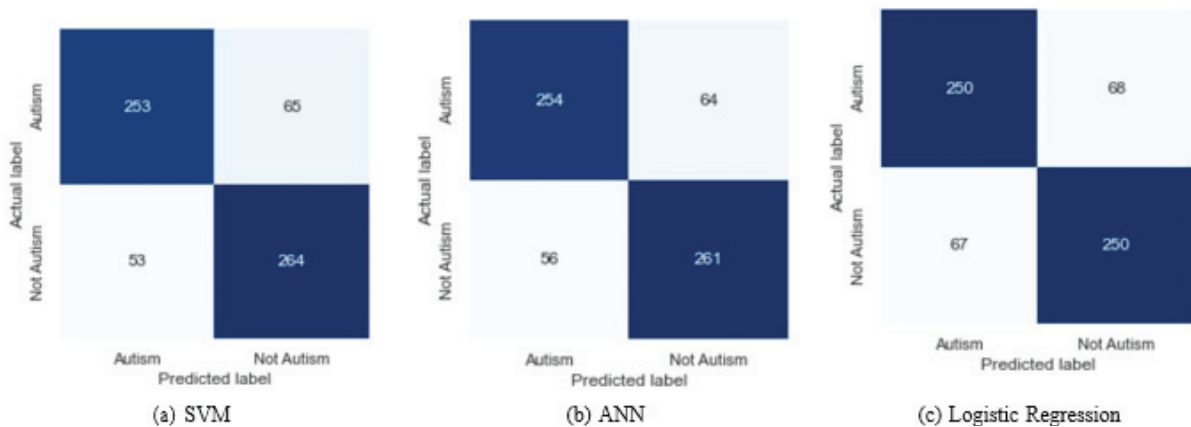


Fig. 1. VGG16 as feature extractor

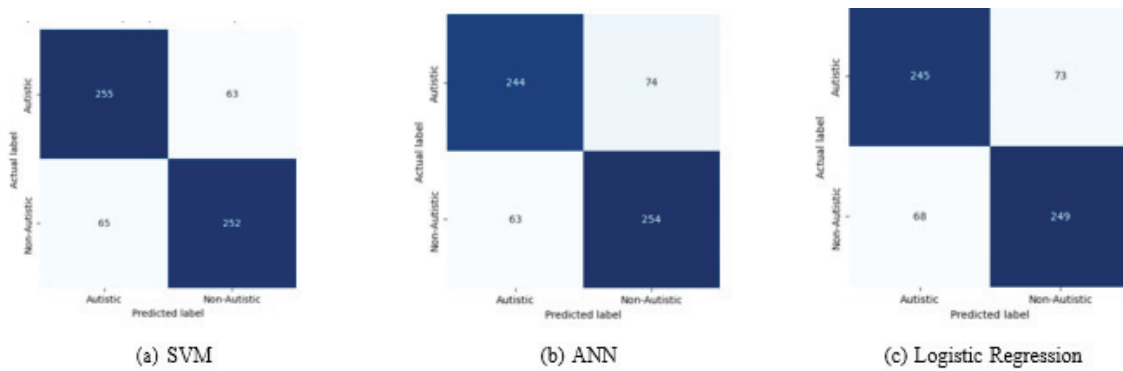


Fig. 2. VGG19 as feature extractor

V. CONCLUSION AND FUTURE WORK

The idea of feature extraction from the face image of the child has been used to illustrate the proposed work. Convolutional Neural Networks (CNN) pre-trained model was used to extract features from photos, and machine and deep learning techniques were employed to detect if the child is suffering from autism or not. The effectiveness of the experiment was evaluated using accuracy, precision, recall, and F-Score. A new method for diagnosing autism using a face image is presented in the current study, which might serve as a form of framework for further research. The maximum accuracy was attained by SVM with GridSearch at 81%, while SVM came in second with an accuracy of 80%. According to these findings, the SVM-based models were successful in correctly categorising kids with ASD (Autism Spectrum Disorder) using facial image characteristics that were retrieved using VGG16. The outcomes for the VGG19 model were in line with those of the VGG16 model. While SVM only obtained an accuracy of 78%, SVM with GridSearch reached an accuracy of 80%. In the future, if enough reliable data are collected, the suggested model could be able to identify between people who have ASDs and others who don't.

REFERENCES

- [1] M. Beary, A. Hadsell, R. Messersmith, and M.-P. Hosseini, "Diagnosis of autism in children using facial analysis and deep learning," 2020.
- [2] B. Banire, D. Al Thani, M. Qaraq, and B. Mansoor, "Face-based attention recognition model for children with autism spectrum disorder," *Journal of Healthcare Informatics Research*, vol. 5, pp. 420–445, 2021.
- [3] F. C. Tamilarasi, R. Vatti, and J. Shanmugam, "Child autism detection based on facial feature classification," *International Journal of Advanced Research in Engineering and Technology*, vol. 11, no. 10, pp. 468–47, 2020.
- [4] R. Sadik, S. Anwar, and M. Reza, "Autismnet: recognition of autism spectrum disorder from facial expressions using mobilenet architecture," *International Journal*, vol. 10, no. 1, pp. 327–334, 2021.
- [5] G. C. Michelassi, H. S. Bortoletti, T. D. Pinheiro, T. Nobayashi, F. R. Barros, R. L. Testa, A. F. Silva, M. C. Revers, J. Portolese, H. Pedrini *et al.*, "Classification of facial images to assist in the diagnosis of autism spectrum disorder," 2021.
- [6] K. K. Mujeeb Rahman and M. M. Subashini, "Identification of autism in children using static facial features and deep neural networks," *Brain Sciences*, vol. 12, no. 1, 2022. [Online]. Available: <https://www.mdpi.com/2076-3425/12/1/94>.
- [7] S. Ganesan, J. Senthil *et al.*, "Prediction of autism spectrum disorder by facial recognition using machine learning," *Webology*, vol. 18, no. Special Issue on Information Retrieval and Web Search, pp. 406–417, 2021.
- [8] M. Elbattah, J.-L. Guérin, R. Carette, F. Cilia, and G. Dequen, "Vision-based approach for autism diagnosis using transfer learning and eye-tracking," pp. 256–263, 2022.
- [9] A. Saranya and R. Anandan, "Facial action coding and hybrid deep learning architectures for autism detection," *Intelligent Automation & Soft Computing*, vol. 33, no. 2, 2022.
- [10] Z. A. Ahmed, T. H. Aldhyani, M. E. Jadhav, M. Y. Alzahrani, M. E. Alzahrani, M. M. Althobaiti, F. Allassery, A. Alshafut, N. M. Alzahrani, and A. M. Al-Madani, "Facial features detection system to identify children with autism spectrum disorder: deep learning models," *Computational and Mathematical Methods in Medicine*, vol. 2022, 2022.
- [11] K. Kaur, C. Singh and Y. Kumar, "Artificial Intelligence Techniques for the Detections of Congenital Diseases: Challenges and Research Perspectives," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 888–893, doi: 10.1109/IC3I56241.2022.10072469
- [12] Kaur, K. Bansal and Y. Kumar, "Artificial Intelligence approaches for Predicting Hypertension Diseases: Open Challenges and Research Issues," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 338–343, doi: 10.1109/IC3I56241.2022.10072978.
- [13] A. Koul, Y. Kumar and A. Gupta, "A Study on Bladder Cancer Detection using AI-based Learning Techniques," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 600–604, doi: 10.1109/ICTACS56270.2022.9988462.