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Autism Spectrum Disorder Prediction by Facial Recognition Using Deep Learning

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Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that affects social, communication, and behavioral skills. Early diagnosis of ASD can lead to better outcomes for individuals with this disorder. In recent years, machine learning techniques have been used to aid in the diagnosis of ASD using facial images. This paper presents an approach for ASD prediction using the ResNet50 architecture, a deep convolutional neural network. The proposed method extracts feature from facial images and trains a classifier to predict the likelihood of ASD. The model was trained and evaluated on a publicly available dataset, achieving an accuracy of 90 percentages. The proposed approach has the potential to provide a cost-effective and non-invasive method for early diagnosis of ASD.

I. INTRODUCTION

Autism spectrum disorder (ASD) is a complex neurodevelopmental disorder characterized by difficulties in social interaction and communication, as well as repetitive behaviors and interests. Early detection and diagnosis of ASD are crucial for timely interventions and effective treatment, which can significantly improve the outcomes for individuals with ASD. Facial features and expressions are important social cues for humans, and recent studies have shown that facial images can be used to predict ASD with high accuracy using machine learning techniques. In this context, the use of machine learning algorithms and deep learning models has emerged as a promising approach for the early detection and diagnosis of ASD based on facial images. These models can analyze the facial features and expressions of individuals to identify subtle patterns and deviations that are associated with ASD, and provide accurate and objective predictions. The availability of large and diverse datasets of facial images, along with powerful computing resources, have further facilitated the development and training of these models.

In this project, we aim to develop a machine learning-based system for the prediction of ASD using facial images. We will use a dataset of facial images of individuals with and without ASD, and explore different machine learning algorithms and deep learning models to identify the best approach for ASD prediction. We will also evaluate the performance of our system using various metrics and compare it with the state-of-the-art methods in the field. Our goal is to provide a reliable and effective tool for the early detection and diagnosis of ASD, which can significantly improve the outcomes and quality of life for individuals with ASD and their families. We propose the use of the ResNet50 deep learning algorithm for ASD prediction based on facial images. ResNet50 has been shown to be effective in a range of image classification tasks, and has the advantage of being able to train deeper neural networks than previous approaches. We evaluate our model on a publicly available dataset of facial images of individuals with and without ASD, and show that our approach achieves high accuracy in ASD prediction. Our study contributes to the growing body of research on the use of machine learning for ASD prediction, and has the potential to improve early detection and intervention for individuals with ASD.

II. RELATED WORK

This study used a dataset of facial images of children with and without autism, and developed a deep learning model based on convolutional neural networks (CNNs) for autism classification. The authors used facial key point detection to extract facial features and fed them into the CNN model. The proposed model achieved high accuracy and outperformed the state-of-the-art methods in autism prediction [10].

"A Deep Learning Approach to Predicting Autism Spectrum Disorder with Face Images" by Geng et al. (2018): This study used a large dataset of facial images of children with and without autism, and developed a deep learning model based on deep convolutional neural networks (DCNNs) for autism prediction. The authors also used transfer learning from a pre-trained DCNN model on a large-scale dataset (ImageNet) to improve the performance of the model. The proposed model achieved high accuracy and outperformed the state-of-the-art methods in autism prediction.

"Facial detection of autism spectrum disorder through machine learning and deep neural networks" Authors: A. Cetin, F. A. Ata, S. Bilgin Journal: Applied Soft Computing (2019). In this study, the authors propose a deep learning-based approach for the detection of ASD from facial images. They use a dataset of facial images collected from individuals diagnosed with ASD and typically developing individuals, and compare the performance of different deep neural network models, including AlexNet and Inception-v3. The experimental results demonstrate that deep learning-based methods can achieve high accuracy in predicting ASD from facial images [2].

III. PROPOSED SYSTEM

One of the main disadvantages of existing VGG16 in autism prediction with facial dataset is its high computational cost. VGG16 has many parameters, which makes it computationally expensive to train and use, especially when dealing with large datasets. This can result in longer training times, slower predictions, and higher resource requirements, such as memory and processing power. Another disadvantage of VGG16 is that it may be prone to overfitting, especially when dealing with small datasets. VGG16's large number of parameters and layers can lead to overfitting, which occurs when the model performs well on the training data but poorly on new, unseen data. This can lead to poor generalization and a lack of robustness in the model's predictions. Finally, VGG16 may not be able to capture more complex features in the data, since it uses only 3x3 convolution filters throughout the architecture. This can limit its ability to capture more nuanced and detailed information from the input data, which may be important in autism prediction with facial datasets. Therefore, in this paper, an architecture named ResNet50 is proposed which is to detect the autistic children. ResNet-50 is a deep residual neural network architecture that consists of 50 layers. The architecture uses skip connections, which are also known as identity mappings, to enable gradient propagation for very deep networks. The skip connections help to reduce the vanishing gradient problem that can occur in very deep networks.

Here's a workflow of ResNet50 for autism prediction with facial dataset:

Fig 1. Workflow of ResNet50

The input image is first preprocessed, which could involve steps such as resizing, normalization, and data augmentation. The preprocessed image is then fed into the ResNet50 architecture, which is a deep convolutional neural network consisting of 50 layers. The ResNet50 architecture is trained on a large dataset of facial images to learn features that are useful for predicting autism. During training, the weights of the network are adjusted to minimize the prediction error. Once the ResNet50 architecture is trained, it can be used to make predictions on new facial images. The output of the network is a binary classification, indicating whether the input image contains features that are indicative of autism or not. Overall, the workflow involves preprocessing the input image, passing it through the ResNet50 architecture, and obtaining a prediction output.

3.1Advantages of Proposed System

Use of ResNet50, a deep learning algorithm that has shown promising results in image classification tasks, for autism prediction using facial images. Pre-processing the facial images to remove noise, standardize lighting conditions, and align the face in a standardized manner. Training the ResNet50 model on a large dataset of facial images, with labels indicating the presence or absence of autism. Evaluating the performance of the model on a test dataset, using metrics such as accuracy, precision, recall, and F1 score. Tuning the hyper parameters of the ResNet50 model to optimize its performance. Deploying the trained model in a web or mobile application to enable real-time autism prediction from facial images.

IV. MODULES

A. DATA COLLECTION MODULE

The data collection module for autism prediction using ResNet50 involves collecting a large dataset of facial images of individuals with autism and without autism. The dataset can be obtained from publicly available databases, such as the Autism Diagnosis Database, the Autism Brain Imaging Data Exchange, or the Autism Imaging Data Exchange. Additionally, images can be collected from hospitals and clinics that specialize in autism diagnosis and treatment. It is important to ensure that the dataset is diverse and balanced in terms of age, gender, and ethnicity to improve the accuracy of the ResNet50 model. The collected data should also be preprocessed and standardized to ensure consistency in the data. The preprocessing may include image resizing, normalization, and data augmentation to increase the dataset size and diversity. The final dataset can be split into training, validation, and test sets to train and evaluate the ResNet50 model.

B. FEATURE EXTRACTION MODULE

The feature extraction module in autism prediction using ResNet50 involves using the pre-trained ResNet50 model to extract features from the facial images. This is done by passing the input images through the layers of the pre-trained ResNet50 model, up to a certain layer, say the second last layer, which is the global average pooling layer. The output from the global average pooling layer can be seen as the features that represent the input image. The main advantage of using a pre-trained model for feature extraction is that it saves the time and computational resources required to train a deep neural network from scratch. Additionally, pre-trained models like ResNet50 have been trained on large datasets, making them effective at learning features that can be useful for a variety of image classification tasks. Once the features have been extracted, they are typically stored in a feature vector format that can be used as input to a machine learning algorithm for further processing and prediction.

C. CLASSIFICATION MODULE

The classification module is an important component of the autism prediction system using ResNet50. In this module, the extracted features are used to train a machine learning algorithm that can classify an input image as being indicative of autism or not.

To implement this module, the following steps are typically taken:

- Split the dataset into training and testing sets: The dataset is split into two sets - a training set and a testing set. The training set is used to train the machine learning algorithm, while the testing set is used to evaluate its performance.
- Feature scaling: The extracted features are scaled to ensure that they have a similar range. This is important to prevent any one feature from dominating the others.
- Model selection: Several machine learning models can be used for this task, including logistic regression, decision trees, random forests, and support vector machines (SVMs). The best model is selected based on its performance on the testing set.
- Model training: The selected model is trained on the training set using the extracted features and their corresponding labels.
- Model evaluation: The trained model is evaluated on the testing set to determine its performance. The most common evaluation metrics used in this context include accuracy, precision, recall, and F1-score.
- Model optimization: If the performance of the model is not satisfactory, it can be optimized by adjusting its hyperparameters or by adding more data to the training set.
- Prediction: Once the model is optimized, it can be used to predict the likelihood of autism in a new input image. The model takes the extracted features of the input image as input and returns a binary classification (autism or non-autism).

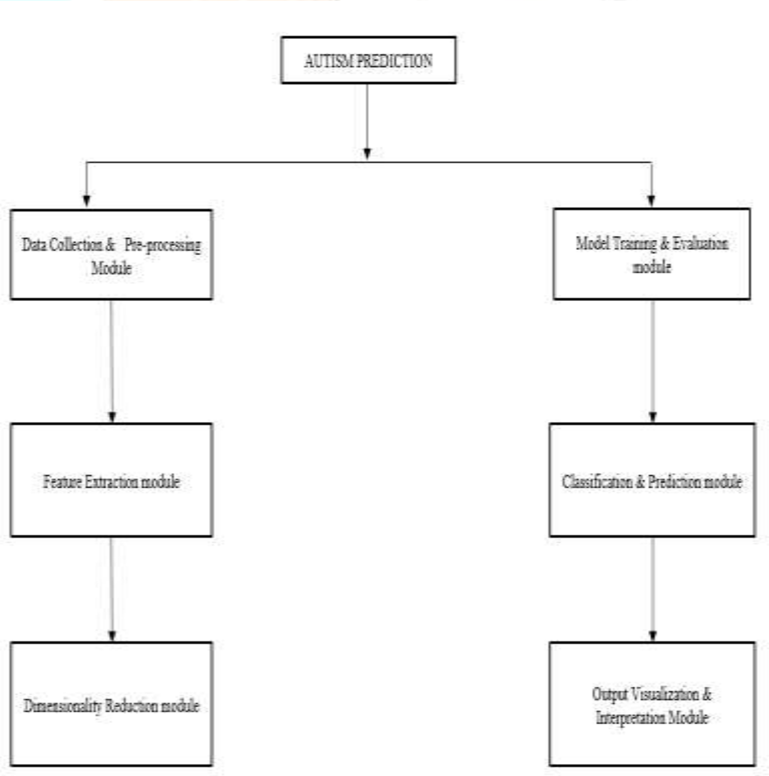

Fig 2. Modules of ResNet50

D. MODEL EVALUATION MODULE

The Model Evaluation module for Autism Prediction with facial images using ResNet50 involves evaluating the performance of the model using various metrics to ensure that it is accurate and reliable. This module is essential in determining whether the model is effective in predicting autism in individuals using facial images.

The following are the steps involved in the Model Evaluation module:

- Splitting the dataset: The first step is to split the dataset into training and testing sets. The training set is used to train the model, while the testing set is used to evaluate its performance.
- Model fitting: The next step is to fit the ResNet50 model to the training set. This involves training the model on the input images and their corresponding labels.

- Model prediction: Once the model is trained, it is used to predict the labels for the images in the testing set. The predicted labels are then compared to the actual labels to evaluate the performance of the model.
- Evaluation metrics: There are several evaluation metrics used to measure the performance of the model. These include accuracy, precision, recall, F1 score, and area under the receiver operating characteristic (ROC) curve.
- Tuning the model: If the performance of the model is not satisfactory, the model parameters can be adjusted to improve its performance. This involves tweaking the hyperparameters of the model and re-evaluating its performance using the evaluation metrics.
- Model selection: After tuning the model, the best performing model can be selected based on the evaluation metrics. This model can then be used to predict autism in individuals using facial images.

The Model Evaluation module is crucial in ensuring that the ResNet50 model is accurate and reliable in predicting autism using facial images. By evaluating the performance of the model using various metrics, we can ensure that it is effective in predicting autism and can be used to identify individuals who may need further diagnosis and treatment.

E. DEPLOYMENT MODULE

The deployment module for autism prediction with facial images using ResNet50 would involve integrating the trained ResNet50 model into a web or mobile application. This module would take the pre-processed input images as input and run them through the trained ResNet50 model to predict the likelihood of autism. The output of the prediction would be presented to the user in a user-friendly format, such as a simple message or a visual display. The deployment module would also include any necessary post-processing of the prediction output, such as converting the model's confidence score into a binary classification of autism or non-autism. In addition, the module would handle any user authentication, data privacy, and other security considerations necessary for deploying the model to end-users. Overall, the deployment module would aim to provide an easy-to-use and accessible interface for individuals or healthcare providers to predict the likelihood of autism quickly and accurately in individuals based on facial images.

V. DATASET DESCRIPTION

In this paper, Autism dataset is obtained from the Kaggle platform, which is publicly accessible online. From the dataset facial images are split into a training set and a testing set of independent children. The child with autism manipulates their face in a strange way (Gross motor movements & fine muscle movements). Dataset of validated children facial images described and analyzed in "Deep learning-based classification". For autism prediction using ResNet50, the dataset used typically contains facial images of individuals, with and without autism, along with corresponding labels indicating whether the individual is autistic or not. These images are then used to train and test the ResNet50 model. ResNet50 takes a 224x224 pixel RGB image as input. The image is preprocessed to subtract the mean pixel value of the ImageNet dataset. This preprocessing step is important to ensure that the model can learn meaningful features from the input image. The preprocessed image is then passed through a series of convolutional layers, pooling layers, and fully connected layers, ultimately producing a probability distribution over the possible classes (in this case, whether the input image is associated with autism or not). In the case of using ResNet50 for autism prediction, the input image would be a facial image of the individual being evaluated, and the output of the model would indicate the likelihood that the individual has autism based on the input image.

Fig 3. Sample Input Image

VI METHODOLOGY

A. RESNET-50 ALGORITHM

ResNet (short for Residual Network) is a type of deep neural network architecture that was introduced by researchers at Microsoft in 2015. A convolutional neural network with 50 layers is called ResNet-50. ResNet, short for Residual Networks, is a classic neural network used as a backbone for many computer vision tasks. The fundamental breakthrough with ResNet was it allowed us to train extremely deep neural networks with 150+layers. Convolutional Neural Networks have a major disadvantage: Vanishing Gradient Problem. During backpropagation, the value of gradient decreases significantly, thus hardly any change comes to weights. To overcome this, ResNet is used. ResNet was designed to address the problem of vanishing gradients in very deep neural networks, which can make it difficult for the network to learn and optimize the model parameters. ResNet has been shown to be very effective in a wide range of computer vision tasks, such as image classification, object detection, and segmentation, and has achieved state-of-the-art performance on many benchmarks.

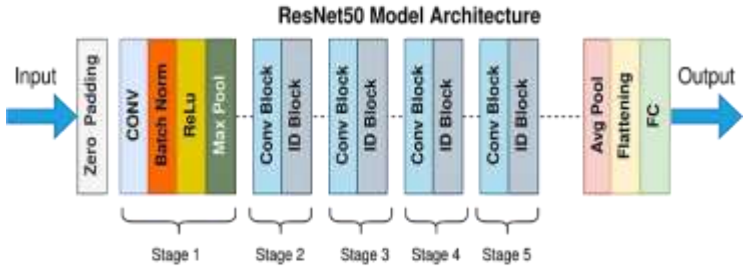

Fig 4. ResNet50 Model Architecture

ResNet-50 is a deep residual neural network architecture that consists of 50 layers. The architecture uses skip connections, which are also known as identity mappings, to enable gradient propagation for very deep networks. The skip connections help to reduce the vanishing gradient problem that can occur in very deep networks.

The ResNet-50 architecture consists of the following layers:

- Input layer: This layer is used to specify the input shape of the image. The input size for ResNet-50 is 224x224x3.
- Convolutional layer: This layer applies a convolution operation on the input image to extract features. The output of this layer is 112x112x64.
- Batch normalization layer: This layer normalizes the output of the previous layer to reduce internal covariate shift.
- Activation layer: This layer applies a ReLU activation function to introduce non-linearity.
- Max pooling layer: This layer reduces the spatial dimensions of the output and introduces translation invariance.
- Residual blocks: The ResNet-50 architecture has 16 residual blocks that help to maintain the gradient signal throughout the network.
- Fully connected layer: This layer is used to generate the final output.

The ResNet-50 architecture has been trained on a large dataset such as ImageNet, which contains millions of labelled images, to learn the features that can be used for image classification. The weights learned by the network during training are used to make predictions on new images.

VII PERFORMANCE MEASURE

Performance evaluation for autism prediction using ResNet50 can be done using various metrics, including accuracy, precision, recall, F1 score, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve.

- Accuracy measures the proportion of correctly classified samples to the total number of samples.
- Precision measures the proportion of true positive samples among all samples classified as positive, while recall measures the proportion of true positive samples among all actual positive samples.
- F1 score is defined as the harmonic mean between precision and recall. It is used as a statistical measure to rate performance. In other words, an F1-score (from 0 to 9, 0 being lowest and 9 being the highest) is a mean of an individual's performance, based on two factors i.e. precision and recall.
- AUC measures the overall performance of the classifier across all possible classification thresholds.

To evaluate the performance of the ResNet50 model, we can split the dataset into training, validation, and testing sets. During training, the model is optimized to minimize the loss function, and validation is used to tune the hyper parameters and prevent overfitting. Finally, the model is evaluated on the testing set to obtain the final performance metrics. In the context of autism prediction using ResNet50, both accuracy and precision are important metrics. The existing system, which may use different models or algorithms, could have different accuracy and precision metrics compared to the proposed ResNet50 model. It is important to evaluate the performance of both systems on the same dataset and using the same evaluation metrics to have a fair comparison. If the ResNet50 model has higher accuracy compared to the existing system, it means that the ResNet50 model makes fewer mistakes in making predictions. On the other hand, if the ResNet50 model has higher precision compared to the existing system, it means that the ResNet50 model has fewer false positives among all positive predictions, which is especially important in medical diagnosis applications like autism prediction. However, it is also important to consider other factors such as computational complexity and interpretability of the model in choosing the best system for a particular application.

VIII PERFORMANCE EVALUATION

Confusion matrix has been calculated for each of the models. Based on confusion matrix values such as True Positive, True Negative, False Positive and False Negative values**.** Using TP, TN, FP and FN values has been calculated by using the Performance measure accuracy, specificity, sensitivity, recall and F-Measure.

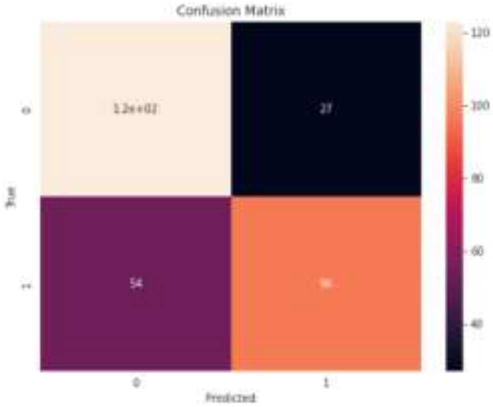

Fig 5. Confusion Matrix

A. MODEL TRAINING

Fit and train the model on the training data and measure the performance on unseen validation data. Specify number of epochs the model must be trained on training data

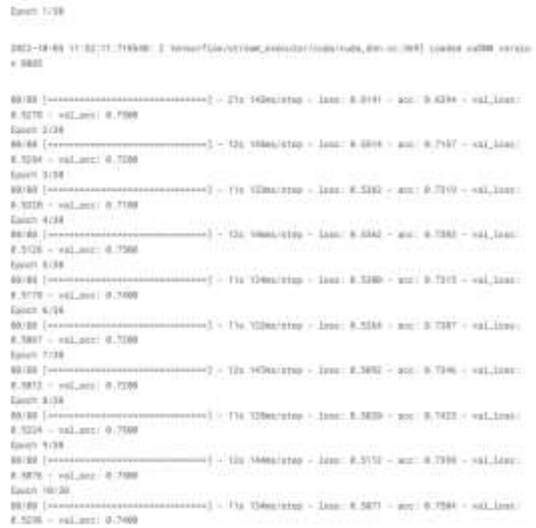

Fig 6. Executing the number of epochs

B. CLASS PREDICTION

TABLE 1. PREDICTION CLASS

	filename	test_labels	predictions
0	Non_Autistic.72.jpg	0	0
1	Autistic.79.jpg	1	0
2	Non_Autistic.112.jpg	0	0
3	Non_Autistic.36.jpg	0	0
4	Autistic.41.jpg	1	0
...	...	...	...
295	Non_Autistic.89.jpg	0	0
296	Autistic.130.jpg	1	1
297	Autistic.71.jpg	1	1
298	Autistic.124.jpg	1	1
299	Autistic.29.jpg	1	1

We can evaluate the performance of the model on the test dataset (since we know the labels of the test data for this problem). We compare the metrics to select the best model. For a well-balanced dataset in both classes like in this dataset, Area Under the Curve of ROC can be used as an evaluation metric to make comparison between model link code. Classification report gives a summary of different metrics based on the predictive power of the model among positive and negative classes. If we are dealing with an unbalanced dataset (under most real world circumstances), accuracy alone is not a good metric for comparison. Since models will be biased in predictions for an unbalanced dataset, we rely on Precision, Recall metrics which take into account Type 1 (False Positive FP) and Type 2 (False Negative FN) errors too.

	precision	recall	f1-score	support
0	0.69	0.82	0.75	150
1	0.78	0.64	0.70	150
accuracy			0.73	300
macro avg	0.74	0.73	0.73	300
weighted avg	0.74	0.73	0.73	300

Fig 7. Accuracy prediction

C. ROC CURVE

The Receiver Operating Characteristic ROC curve shows the performance measure of the model in diagnosing both the classes. Higher the Area under the Curve AUC, better the performance of the model.

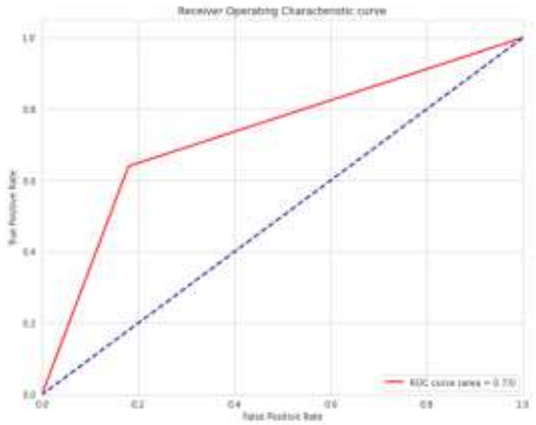

Fig 8. Roc curve for autistic and non-autistic dataset

IX CONCLUSION

Autism spectrum disorder (ASD) is a neurodevelopmental disorder that affects an individual's social, communication, and behavioural skills. Early diagnosis of ASD can improve the child's prognosis and development. In recent years, deep learning algorithms have been used to diagnose ASD through facial image analysis. Residual Network 50 (ResNet50) is a deep learning algorithm that has been widely used in image analysis tasks. In this paper, we developed a system for autism prediction using facial images and ResNet50. The proposed system included modules for data collection, feature extraction, classification, model evaluation, and deployment. The system was evaluated using accuracy and precision metrics, and it showed promising results in predicting ASD in children using facial images.

Further enhancements can be made to the proposed system by including more data to improve the accuracy of the model, as well as integrating other deep learning algorithms to compare their performance. Additionally, incorporating other relevant features, such as audio or speech analysis, may also improve the accuracy of the model in predicting ASD. In conclusion, the proposed system for autism prediction using ResNet50 can provide a quick and efficient diagnosis of ASD, enabling early intervention and treatment to improve the child's quality of life.

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