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AUTISM DESEASE DETECTION USING TRANSFER LEARNING TECHNIQUES

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ABSTRACT

Social media data and biological pictures may be used to diagnose autism spectrum disorder (ASD), a kind of mental disease. Autism spectrum disorder (ASD) is a neurodevelopmental illness that alters the facial appearance as a person matures. Autism spectrum disorder (ASD) children are easily distinguishable from normally developing (TD) youngsters due to noticeable differences in facial landmarks. The planned study is novel since it would use facial recognition and social media to identify people with autism spectrum disorder. While deep learning approaches hold promise for identifying such landmarks, doing so would need very accurate technology for extracting and creating the appropriate patterns of facial data. This research aids communities and psychiatrists in experimentally identifying autism using face traits by using a simple web application built on a deep learning system, namely, a convolutional neural network with transfer learning and the flask framework. The classification challenge was performed using the pretrained models Xception and Resnet50. The few face photos used to evaluate these models were gathered via the Kaggle site.

Keywords: Learning Transfer, Autism Neural Network, ResNet50, Xception

1.INTRODUCTION

Autism spectrum disorders (ASD) have a broad variety of symptoms and severities, as the name "spectrum" suggests. These conditions include autism, childhood disintegrative disorders, and Asperger's syndrome. These conditions are now classified as pervasive developmental disorders in the International Statistical Classification of Diseases and Related Health Problems (ICD). Lack of eye contact, a lack of responsiveness to name calling, and a lack of interest in caregivers are some of the initial signs of autism spectrum disorder (ASD) that may show during the first year of life. Some infants and toddlers seem to grow normally during the first year, then begin displaying autistic traits, such as restricted and repetitive patterns of behavior, a narrow range of interests and hobbies, and poor language abilities, between the ages of 18 and 24 months [1]. In the first five years of life, children with these diseases may abruptly become reclusive or violent as they struggle to connect and communicate with society due to their challenges. Although autism spectrum disorder (ASD) symptoms first manifest in infancy, they often continue into later years. We showed that a well-trained classification algorithm (based on transfer learning) may be used to identify autistic traits in a child's photo. The widespread availability of high-definition cameras in smartphones means that this model may quickly give a diagnostic test of potential autistic features. Two pre-trained deep learning algorithms (Resnet50 and Xception) were applied to the problem of ASD identification.

Two pre-trained deep-learning algorithms were used, and Resnet50's results were the most promising. A method was developed to aid medical professionals in ASD diagnosis using facial and eye recognition [2]. The growing system has been verified and investigated via a number of channels.

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2.LITERATUREREVIEW

Learning based pattern classifiers, including deep networks, have shown impressive performance in several application domains, ranging from computer vision to cybersecurity. It has also been shown that skillfully prepared hostile input perturbations during training or testing may readily spoof its predictions [3]. The subject of study known as adversarial machine learning examines how vulnerable machine learning systems are to such crazy patterns (also known as adversarial instances) and how to best protect against them. In this paper, we provide a comprehensive overview of the development of this field of study over the past decade and beyond, from the earliest, pioneering work on the security of non-deep learning algorithms to the most recent, focused on comprehending the security properties of deep learning algorithms, in the context of computer vision and cybersecurity [4]. We document intriguing links between these seemingly unrelated fields of study, drawing attention to prevalent misunderstandings about how to evaluate the security of machine learning algorithms. We cover the fundamental constraints of existing work, as well as the associated future challenges towards the construction of more secure learning algorithms, and examine the main threat models and attacks developed to this goal [5].

3.PROPOSED SYSTEM

Our suggested system was developed using a transfer learning strategy, with a convolutional neural network serving as the meta-learner and heterogeneous weak learners serving as the basis models. Xception, Resnet-50, were used as the heterogeneous base models, which took in three-dimensional images as inputs. Data was separated differently than in the past, with 60% going toward training, 10% toward validation, and 30% toward testing. Overfitting may have been prevented during meta-learner training without this tweak. The meta-learner was able to produce correct probabilities at Level 0 since the projected dataset included a probability of expected values. The final model (meta-learner) was constrained using both the validation dataset and the outputs to avoid
overfitting. The level1 prediction was the ultimate result. The transfer learning model produced a final model(meta-learner) by using the predicted results from several other models. The transfer learning model produced a final model by using the predicted results from several other models. There is bias and instability in the single neural network model when it comes to the data. Therefore, alternative models were selected during the first model development phase.

4.SYSTEM ARCHITECTURE

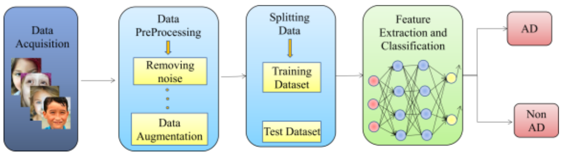

Fig4.1:SystemArchitecture

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5.RESULTS

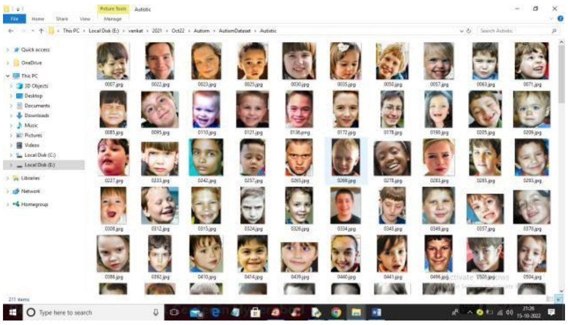

Fig5.1:DataSet

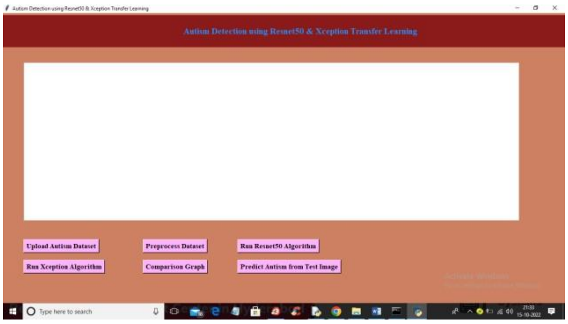

Fig5.2:OutputScreen

In above screen click on ‘Upload Autism Dataset’ button to upload dataset and get below out put

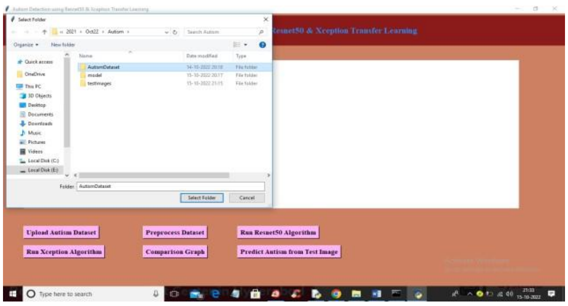

Fig5.3:OutputScreen

In above screens electing and uploading ‘Autism Dataset’ folder and then click on ‘Select Folder’ button to load dataset and get below output.

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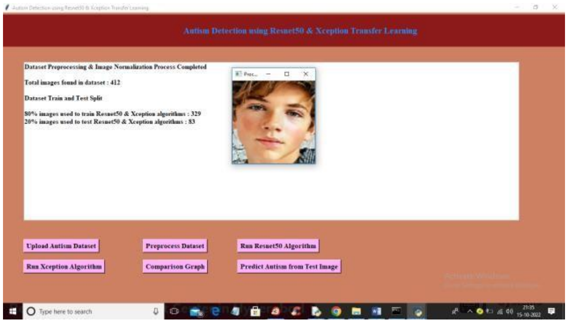

Fig5.5:OutputScreen

In above screen dataset processed and to check weather images processed properly I am showing sample image and now close above image and we can see dataset contains 412 images where application using 329 images for training and 83 For testing. Now click on ‘Run Resnet50 Algorithm’ button to train Resnet50 and get below output

Fig5.6:OutputScreen

In above screen Resnet50 training completed and we got accuracy as 96% The y-axis of the matrix displays the actual classes, whereas the x-axis reflects the classes that were predicted. Resnet50 only predicts 3 records as improperly predicted, as seen in the following graphs where identically colored boxes indicate inaccurate predictions and uniquely colored boxes represent accurate ones. The above graph may be closed, and the 'RunXceptionAlgorithm' button can be used to train Xception, producing the results shown below.

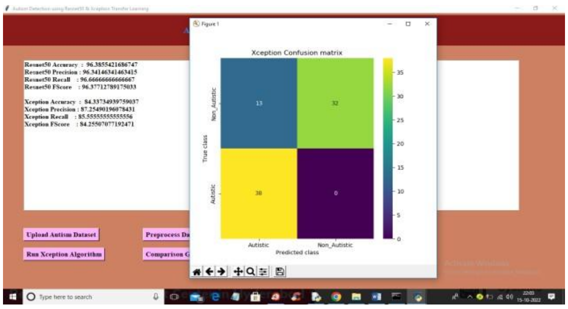

Fig5.7:OutputScreen

In above screen Xception training completed and with Xception we got 84%accuracy and in confusion matrix graph we can see Xception predict 13 records incorrectly. So, from

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both algorithms Resnet50 got high accuracy. Now click on ‘Comparison Graph’ button to get below graph.

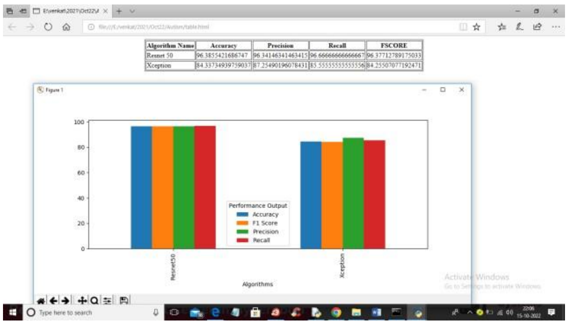

Fig5.8:OutputScreen

In above graph x-axis represents algorithm names and y-axis represents accuracy, precision, recall and F1SCORE in different colour bars. In above graph we can see Resnet50 got high performance. Now close above graph and the ‘clickon ‘Predict Autism from Test Image’ button to upload test image and get below output.

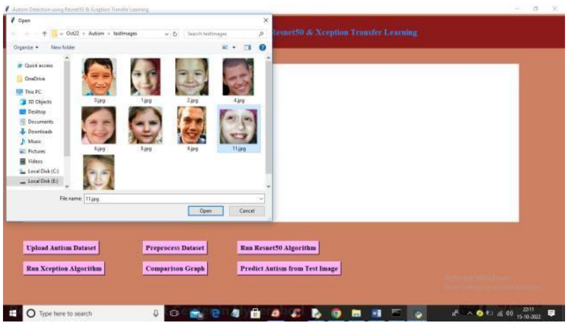

Fig5.9:OutputScreen

In above screen selecting and uploading ‘11.jpg’ and then click on ‘Open’ button to get below prediction output.

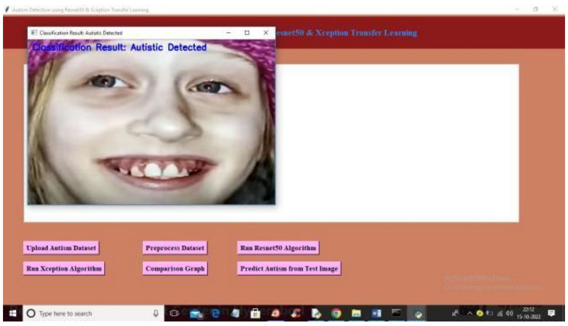

Fig5.10:OutputScreen

In above screen image is classified as ‘Autistic Detected’ and now upload other image and get output

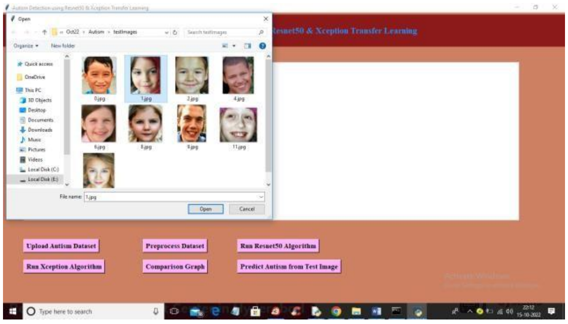

Fig5.11:OutputScreen

In above screen selecting and uploading '1.jpg' and then click on 'Open' button to upload image and get below output

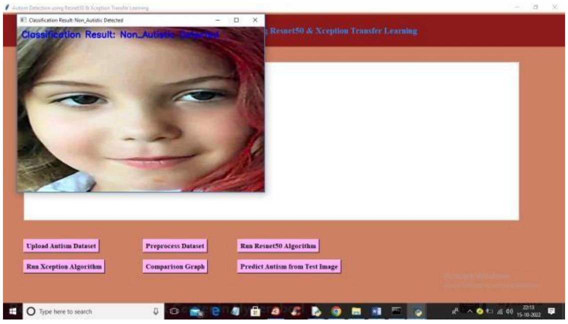

Fig5.12:OutputScreen

In above screen image is classified as 'NonAutistic'. Similarly, you can upload and test other images.

CONCLUSION

Improvements in medical science and technology throughout the world have sparked a renewed focus on autism in children. Researchers and academics have ramped up their efforts in recent years as the number of children diagnosed with autism has risen. This is so that those with autism can receive the early diagnosis and behavioral development treatment programs that will hopefully allow them to leave the realm of autism and become more fully integrated into society. This paper evaluated the performance of three deep learning models in detecting ASD through facial features: Xception, Resnet50. Classification accuracy was greatest at 91% for the Xception model and 98% for the Resnet50 model, both of which were trained using freely accessible datasets on the Internet.

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