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AUTISM DETECTION USING RESNET50 & XCEPTION TRANSFERLEARNING

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ABSTRACT

Autism spectrum disorder (ASD) is a type of mental illness that can be detected by using social media data and biomedical images. Autism spectrum disorder (ASD)is a neurological disease correlated with brain growth that later impacts the physical impression of the face. Children with ASD have dissimilar facial landmarks, which set them noticeably apart from typically developed (TD) children. Novelty of theproposed research is to design a systemthat is based on autism spectrum disorder detection on social media and face recognition. To identify such landmarks, deep learning techniques may be used, but they require a precise technology for extracting and producing the properpatterns of the face features. This studyassists communities and psychiatrists in experimentally detecting autism based on facial features, by using an uncomplicated web application based on a deep learning system, that is, a convolutional neural network with transfer learning and the flask framework. Xception, and Renet50 are the pretrained models that were used for the classification task. The dataset that was used to test these models was collected from the Kaggle platform and consisted of few face images. Standard evaluation metrics such as accuracy, specificity, and sensitivity were used to evaluate the results of the three deep learning models. The Xception model achieved the highest accuracy result of 91% and Resnet50model (98%).

Keyterms : Autism Disease, Neural Network, Resnet50 and Xception Transfer Learning.

1.INTRODUCTION

Autism spectrum disorders (ASD) refer to a group of complex neurodevelopmental disorders of the brain such as autism, childhood disintegrative disorders, and Asperger's syndrome, which, as the term "spectrum" implies, have a wide range of symptoms and levels of severity . These disorders are currently included in the International Statistical Classification of Diseases and Related Health Problems under Mental and Behavioral Disorders, in the category of Pervasive Developmental Disorders . The earliest symptoms of ASD often appear within the first year of life and may include lack of eye contact, lack of response to name calling, and indifference to caregivers. A small number of children appear to develop normally in the first year, and then show signs of autism between 18 and 24 months of age , including limited and repetitive patterns of behavior, a narrow range of interests and activities, and weak language skills. As these disorders also affect how a person perceives and socializes with others, children may suddenly become introverted or aggressive in the first five years of life as they experience difficulties in interacting and communicating with society. While ASD appears in childhood,it tends to persist into adolescence and adulthood .

Our study demonstrated the use of a well- trained classification model (based on transfer learning) to detect autism from an image of a child. With the advent of high- specification mobile devices, this model can readily provide a diagnostic test of putative autistic traits by taking an image with cameras. The main contributions of our research are as follows:

i. Two pre trained deep learning algorithms were applied for ASD detection: Resnet 50, Xception.

ii. The Resnet50 model showed the best performance of the two pre trained deep learning algorithms

iii. A system was designed to help health officials to detect ASD through eye and face identification

iv. The developing system has been validated and examined using various methods.

2.LITERATURE REVIEW

Learning-based pattern classifiers, including deep networks, have shown impressive performance in several application domains, ranging from computer vision to cybersecurity. However, it has also been shown that adversarial input perturbations carefully crafted either at training or at test time can easily subvert their predictions. The vulnerability of machine learning to such wild patterns (also referred to as adversarial examples), along with the design of suitable countermeasures, have been investigated in the research field of adversarial machine learning. In this work, we provide a thorough overview of the evolution of this research area over the last ten years and beyond, starting from pioneering, earlier work on the security of non-deep learning algorithms up to more recent work aimed to understand the security properties of deep learning algorithms, in the context of computer vision and cybersecurity tasks. We report interesting connections between these apparently-different lines of work, highlighting common misconceptions related to the security evaluation of machine-learning algorithms. We review the main threat models and attacks defined to this end, and discuss the main limitations of current work, along with the corresponding future challenges towards the design of more secure learning algorithms.

3.PROPOSED SYSTEM

We utilized the transfer learning approach to develop our proposed system, which involved convolutional neural network as the meta-learner and heterogeneous weak learners as the base models. Xception, Resnet-50, were used as the heterogeneous base models, which took in three- dimensional images as inputs. The data separation process differed from that of traditional models, with 60% of the data being used for training, 10% for validation, and 30% for testing. This modification was necessary to avoid overfitting during the meta-learner training phase. The predicted dataset from Level 0 already contained a probability of expected values, enabling the meta-learner to provide accurate probabilities from Level 0. To prevent overfitting, the final model (meta-learner) was trained using both the validationdataset and the outputs. The level 1 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 thepredicted results from several other models.However, the single neural network model demonstrates bias and volatility toward the dataset. As a result, different models were chosen whenconstructing the base model.

4.SYSTEM ARCHITECTURE

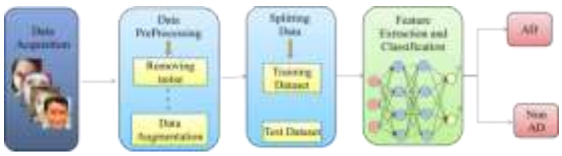

Fig 4.1: System Architecture

5.RESULTS

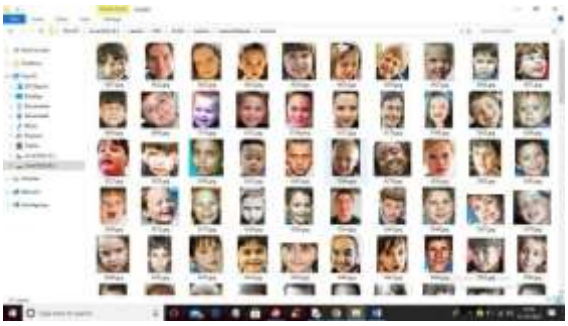

Fig 5.1: DataSet

Fig 5.2: Output Screen

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

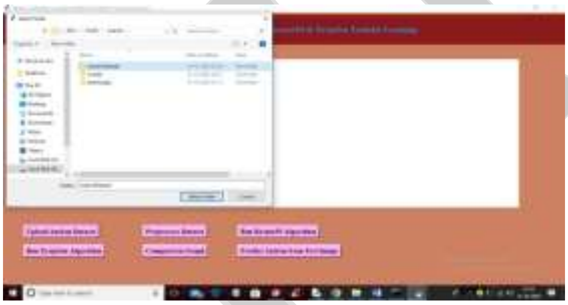

Fig 5.3 : Output Screen

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

Fig 5.4 : Output Screen

In above screen dataset loaded and now click on ‘Preprocess Dataset’ button to read and process all images and get below output

Fig 5.5 : Output Screen

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 Resnet50Algorithm’ button to train Resnet50 andget below output

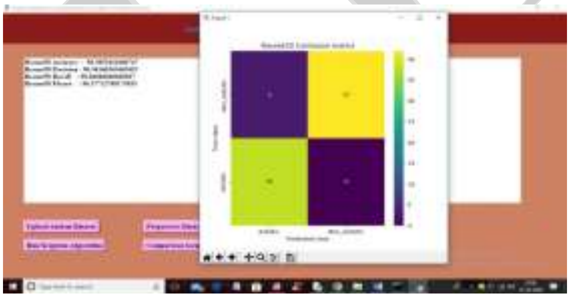

Fig 5.6 : Output Screen

In above screen Resnet50 training completed and we got accuracy as 96% and in confusion matrix graph x-axisrepresents PREDICTED classes and y-axisrepresents TRUE CLASSES. In abovegraph same colour boxes representsINCORRECT prediction count and different colour boxes represents CORRECT prediction count and Resnet50 predict only 3 records as incorrectly. Now close above graph and the click on ‘Run Xception Algorithm’ button to train

Xception and get below output

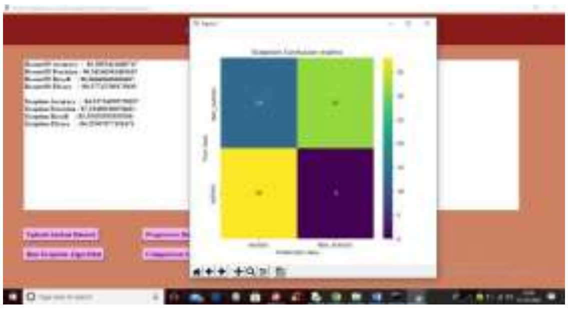

Fig 5.7 : Output Screen

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 both algorithms

Resnet50 got high accuracy. Now click on 'Comparison Graph' button to get below graph

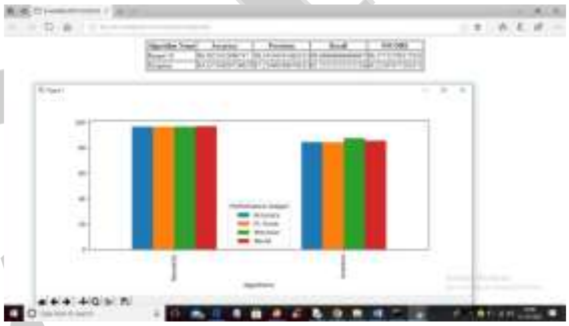

Fig 5.8 : Output Screen

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 then click on 'Predict Autism from Test Image' button to upload test image and get below output

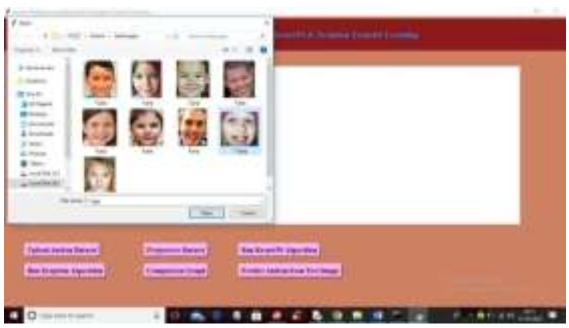

Fig 5.9 : Output Screen

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

Fig 5.10 : Output Screen

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

Fig 5.11 : Output Screen

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

Fig 5.12 : Output Screen

In above screen image is classified as ‘Non Autistic’. Similarly you can upload and test other images

6.CONCLUSION

Interest in child autism has risen due to the advances in global health know-how and capacities. Moreover, the number of autistic children has increased in recent years, due to which researchers and academics have intensified their efforts to uncover the causes of autism and to detect it early in order to give autistic people behavioral development treatment programs that should help them integrate into society and leave the isolation of the autistic world.

This paper evaluated the performance ofthree deep learning models in detecting ASD through facial features: Xception, Resnet50. Each model was trained on apublicly available dataset on the Internet, and the best result for classification accuracy was achieved by the Xception model (91%) and Resnet50 model (98%). The results of the model classification showed us the possibility of using such models based on deep learning and computer vision as automatic tools for specialists and families to accurately and more quickly diagnose autism. Computer techniques contribute to the successful conduct of complex behavioral and psychological analyses for autismdiagnosis that require a longer time andgreat effort.

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