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“A CONVOLUTIONAL NEURAL NETWORK MODEL FOR EARLY STAGE DETECTION OF AUTISM SPECTRUM DISORDER USING DEEP LEARNING”

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Abstract: Autism spectrum disorder (ASD) is a neurological disorder that begins in childhood and lasts the rest of person’s life. It has an influence on how a person communicates and learns, as well as how they act and connect with others. There are number of techniques that can be used to help the child to grow and acquire new abilities. Behavioural and communication therapy, skill training, and symptom-controlling medications are all options available for treatment which are time consuming and subjective. Therefore, early and accurate detection of ASD is required which will help in treatment planning. With the patient’s history and different medical tests, the brain MR scans can proceed towards the distinguish between the Typical controls (TC) and ASD controls. The work is towards the development of Computer Aided Diagnosis for ASD detection and its classification into Typical Control (TC) and ASD. This project is about the selection of CNN deep learning techniques for accuracy improvement. In this project we have used total 10878 image belongings to typical control and autism. The collected datasets are pre-processed and applied convolution neural network with four layers which is giving 99% accuracy for training and validating data.

Keywords: Autism Spectrum Disorder (ASD), Deep Learning, Classification, Convolutional Neural Network (CNN).

I. INTRODUCTION

A neuro-developmental disease called autism spectrum disorder (ASD) exists. The most common signs of neuro developmental disorders include hyperactivity, a lack of social communication, a lack of language and learning, and a lack of learning. An article on neurodevelopmental disorders, as well as a thorough assessment of ASD and other disorders, was released by America's Children and the Environment (ACE). Genetics, chemicals found in certain foods, or environmental factors can all contribute to ASD. Children with ASD are more prevalent than ever, with a ratio of 1:68. A diagnosis of ASD can be made for a person; depending on the number of children and the severity of the ASD, this may take two or three days.

By examining a child's behaviour, numerous streams of clinicians do a manual diagnosis process. Actually, manual diagnosis can identify ASD in children as young as 3 years old or older. Benefits of treatments initiated at this level take a very long time to manifest. Numerous studies have been conducted over the last few years to hasten diagnosis so that ASD can be identified at an early age, improving the mechanism of treatment. Deep learning is one method that has been used by researchers to tackle this problem; it is effective and dependable at detecting ASD with little processing time. With the help of historical data, machine learning can be used to train a system to predict ASD in a timely manner.

Unsupervised and supervised deep learning can be generically characterised. Supervised learning, which employs a rule-based methodology and analyses empirical data sets to create precise predictive models, is more suited and accurate in predicting ASD. There are numerous supervised learning algorithms available. In this research, the effective algorithms are found, taken into account when recognising neural networks, and applied to data on the autism spectrum that has been obtained by ABIDE from a repository.

This project has revealed the outcomes of these algorithms' use of neural networks on an autism dataset. Analysis of these precise findings was done in order to help people predict autism spectrum disorder (ASD) early on and make wise judgments. Thus, by enhancing their behavioural and social skills through early autism intervention employing deep learning approaches, autistic people have a fresh opportunity to lead better lives. emotive capabilities. The ASD, deep learning, supervised learning, analysis procedure, and outcome analysis are covered in the sections that follow.

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II. LITERATURE REVIEW

Md Rishad Ahmed and Md Shale Ahammed [1] This model was implemented and uses Support Vector Machines (SVM) to separate ASD patients from healthy controls and Restricted Boltzmann Machines (RBM) to extract features from fMRI data. They undertake a number of data processing processes beforehand, including suitable slice time correction and normalisation. On a dataset made up of 105 Typical Control (TC) and 79 ASD participants from the renowned database ABIDE [Autism Brain Imaging Data Exchange], they implemented their methodology. They mostly use extracted information from deep learning as input to the SVM to converge the classification of ASD. They achieved an F1 score of 80.50 percent and accuracy of 83 percent. They believe that ML classifiers with DL-based feature extraction could improve clinical diagnosis and treatment of ASD. Future plans call for expanding the amount of data available as well as developing fresh deep learning models that can pinpoint ASD onset abnormalities.

Dr U B Mahadevaswamy, Rachana M and Rohan R [2] Proposes a system presents a technique for autism identification using structural brain MRI data from two datasets and a well-trained machine learning algorithm. Random forest and logistic regression were used as the foundation for the prediction. These techniques produced accuracy results of 0.82 and 0.80, respectively, which are significantly better than the results of the earlier investigations. The results from earlier studies were used as part of the pre-processing for the VBM analysis, and they presented a trustworthy method for autism detection. By using 3-D MRI as an input for the machine learning model VBM, this work can be further enhanced. Further analysis can be done to determine the parametric findings based on the subjects' ages and genders, and rendering can also be done to the 2-D glass brain results to provide 3-D outcomes.

Qaysar Mohi-ud-Din and A K Jayanthy [3] Proposes a system trained the pre-trained CNNs, GoogleNet, and SqueezeNet for ASD classification using a transfer learning approach. Using the EEG signals of both individuals and healthy controls. Using the GoogLeNet and SqueezeNet, it was possible to classify the scalograms produced from the EEG signals of ASD patients and healthy control participants with 75 percent and 82 percent accuracy, respectively.
The classification of ASD cases and control participants using EEG data was done in this work utilising a transfer learning approach, which produced good accuracy and outcomes. The single CPU used to conduct this study resulted in a longer training period, which is one of its disadvantages. Several additional pretrained neural networks might be employed to classify the ASD cases and normal participants, and the dataset size could also be expanded.

Sakib Mostafa, Lingkai Tang and Fang-Xiang Wu [4] Proposes a system have created brain network-based ASD diagnostic characteristics. In particular, they have built a brain network from a brain functional magnetic resonance imaging using the 264 regions based parcellation approach (fMRI). Then, they defined three more features by network centralities, and 264 raw brain characteristics by the 264 eigenvalues of the brain network's Laplacian matrix. 64 discriminating characteristics have been obtained by using a feature selection technique. Additionally, they used our characteristics from the ABIDE (Autism Brain Imaging Data Exchange) dataset to build a number of machine learning models for detecting ASD. With the help of our derived features, the linear discriminant analysis was able to classify the data with a classification accuracy of 77.7 percent, outperforming the most recent findings. On the basis of rs-fMRI pictures, they have suggested a set of new features for machine learning algorithms to diagnose ASD. After using a feature selection algorithm, they outperformed state-of-the-art techniques in terms of accuracy, and this enabled machine learning algorithms perform better. Our suggested features should be combined with more sophisticated machine learning methods like reinforcement learning and deep learning to create stronger categorization models.

B.Pugazhenthi [1], and G.S.Senapathy [2] [5] Proposes a system work included The Autism Brain Imaging Data Exchange database, which includes both typical and autistic images, is where MRI brain scans are gathered. Cerebrospinal fluid, white matter, and grey matter are three types of segmented brain tissue. The intensity levels of these tissues are used to classify them, with white matter having the highest intensity value. The lowest intensity value is found in cerebrospinal fluid. These tissues are essential for making remedial decisions and assessing the possibility of the flaws According to the segmentation results, there is a higher concentration of white matter in the autism image than there is in a normal image. The Deep Neural network classifier classified the photos of the autism brain using both segmented and original images. A single GPU and 4GB of RAM are used to run the classifier in this setting. It is trained on 40 photos, and after six validation iterations, an accuracy value of 82.61 percent is obtained.
The categorization results provided by the suggested Alexnet architecture have an accuracy of 82.61 percent. According to the measured volumes, it is also seen that autism patients have larger brains than healthy individuals. Finally, it is determined that the two variables that can be used to diagnose the autism defect are an increase in the volume of the brain and a high concentration of white matter.

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Yuqing Song, Thomas Martial Epalle and Hu Lu [6] This Work contains a new analysis method to spot ASD-related changes to community patterns in functional networks. Additionally, utilising solely community pattern quality measurements as features, we develop machine learning classifiers to forecast the clinical class of patients with ASD and controls. According to analyses of 235 persons, including patients with ASD and controls who were age-matched, from six publically accessible datasets, the modular organisation is severely altered in people with ASD. Peak accuracy for in-site data is 85.16 percent, and for multisite data it is 75.00 percent.
They demonstrated that the modular structure's discriminative capacity, as represented by the chosen metrics, is relatively strong, supporting the dysconnectivity theory of this disorder, for which network connectivity patterns are being looked at more and more as prospective biomarkers.

Osman Altay and Mustafa Ulas [7] proposes a system Children aged 4 to 11 years were diagnosed with ASD using a categorization technique. For classification, the K-Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) methods are employed. 30% of the data set was chosen as test data and 70% as training data for the algorithms. As a result of the work, the accuracy of the LDA method is 90.8 percent, compared to 88.5 percent for the KNN approach. The ASD disease classification approach was used to attempt to diagnose kids between the ages of 4 and 11 years old. The study made use of a dataset comprising a variety of questions. The classification techniques employ the LDA and KNN algorithms. The only modification made to the data is to turn it into numerical values. In order to compare this study to the next ones, the values of TP, TN, FP, and NP are determined as well as the values of accuracy, sensitivity, specificity, and precision for the F-measure.

Md. Fazle Rabbi and S. M. Mahedy Hasan [8] proposes a system Children with autism can now be identified using artificial intelligence systems using photographs that are unusable to most people. In order to categorise children with autism spectrum disorder (ASD), we have utilised five different algorithms: Gradient Boosting Machine (GBM), Multilayer Perceptron (MLP), Random Forest (RF), and AdaBoost (AB), and Convolutional Neural Network (CNN). When comparing the categorization results of various algorithms, we found that CNN had the highest accuracy, at 92.31 percent.

Anibal Sólon Heinsfeld and Alexandre Rosa Franco [9] Social difficulties and repetitive behaviours are hallmarks of ASD, a brain-based condition. One in every 68 children in the United States has ASD, according to recent statistics from the Centers for Disease Control. In an effort to understand the neural patterns that arose from the classification, they looked into functional connectivity patterns that can be used to definitively identify ASD patients in functional brain imaging data. By correctly identifying ASD patients in the dataset with 70% more accuracy than control patients, the results advanced the state-of-the-art. The findings demonstrate that the algorithm used performed better than that of earlier studies of people with autism spectrum condition identified using ABIDE multi-site resting-state brain activation. The Supplementary material contains results obtained utilising several brain parcellations. By using autoencoders to make the data less dimensional, the outcomes for SVM classifications remained consistent. They used SVM without fine-tuning on a smaller set of dimensions discovered by auto encoders.

Xia-an Bi and Yang Wang [10] To discriminate between TC and ASD, the random SVM cluster was suggested. The results demonstrate that this method has outstanding feature-based classification performance. Furthermore, based on the ideal feature set, accuracy might be as high as 96.15 percent. Additionally, abnormal brain areas such the precuneus, hippocampus, and inferior frontal gyrus (IFG) (orbital and opercula portion) could be identified. It is suggested that the random SVM cluster method may be used to make an auxiliary diagnosis of ASD. They suggested a unique approach, random SVM cluster, which performs better at classifying patients with ASD from those with TD (accuracy is 96.15 percent). However, it also has some restrictions. First off, they could use voxel level features in future research as we only used brain level features in this one. Second, the only features included in our analysis were four graph metrics. More categories of graph metrics could be used as features in further investigations. The random SVM cluster has outstanding performance based on just one modal feature, but future studies may improve its performance by adding multi-modal features.

III. EXISTING SYSTEM

Since there are no biomarkers used in clinical practise for the diagnosis of autism, it presents unique difficulties for healthcare professionals (HCPs) compared to other neurodevelopmental disorders and the majority of psychiatric disorders.
The condition also has a wide range of severity levels and symptom manifestation, and traits that are typical of autism can appear in people with different illnesses. One of the important areas of medical research is the identification of people on the autism spectrum. The prediction of autism spectrum disorders is not automated.

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The current system makes use of machine learning techniques including Decision Tree
The findings of comparing the performance of the aforementioned techniques based on their execution times using Tree, K-Nearest Neighbour, and Naive Bayes Classifier were unreliable.

IV. PROPOSED SYSTEM

The proposed system automates the prediction of the autism spectrum using deep learning methods. The goal of this approach is to launch a deep learning-based framework with the CNN VGG16 algorithm and carry out the investigation for the classification of ASD in MRI brain images. We will gain some understanding of the neural dysfunction in autistic children thanks to this effective deep learning process, which will also aid in diagnosing autism in children in its early stages.
Using a deep-learning model, we have obtained some preliminary findings on the detection of AUTISM positive cases using MRI brain scans. On the same Brain-MRI-dataset, we had to show a considerable improvement in performance over Autism, the only publicly maintained tool for classifying AUTISM positive MRI Brain pictures.
Despite the modest size of the publicly accessible dataset, the results are encouraging. We intend to use larger AUTISM MRI Brain imaging datasets and clinical studies to further validate our method.

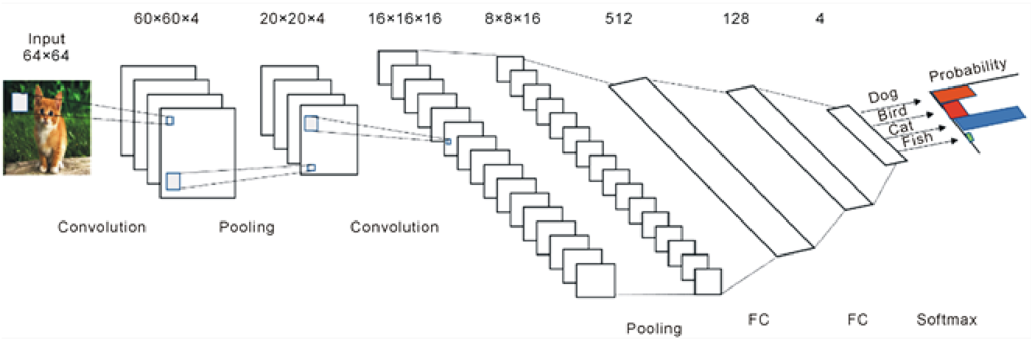

Fig. 1 Working of CNN layers

Convolutional Neural Networks have the following layers:
- Convolutional Layer
- ReLU Layer
- Pooling Layar
- Fully Connected Layer

Step 1: Convolutional Layer
In order to summarise the existence of features that have been found in the input, convolutional neural networks apply a filter to create a feature map.

Step 2: ReLU Layer
All negative values from the filtered photos are removed and replaced with zeros in this layer. In order to prevent the values from adding up to zero, it is happening.
Rectified Linear unit (ReLU) Transform functions only turn on a node if the input value is higher than a specific limit. When the information surpasses a threshold, the output departs from zero while the data is below zero. It and the dependent variable are related linearly.

Step3: Pooling Layer
We lessen the layer's picture stack's size. Pooling is finished after passing through the activation layer. We accomplish this by following the four steps shown below:
- Pick a window size (often 2 or 3)
- Pick a stride (usually 2)
- Walk your Window across your filtered images
- From each Window, take the maximum value

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Step4: Fully Connected Layer

Every neuron in the network's final layer is connected to every other neuron in the layers before and after, which is referred to as the network being fully interconnected.

This simulates higher-level reasoning in which all potential routes from the input to the output are taken into account.

Take the reduced picture and insert it into the single list after it has undergone two layers of convolution relo and pooling and been turned into a single file or a vector.

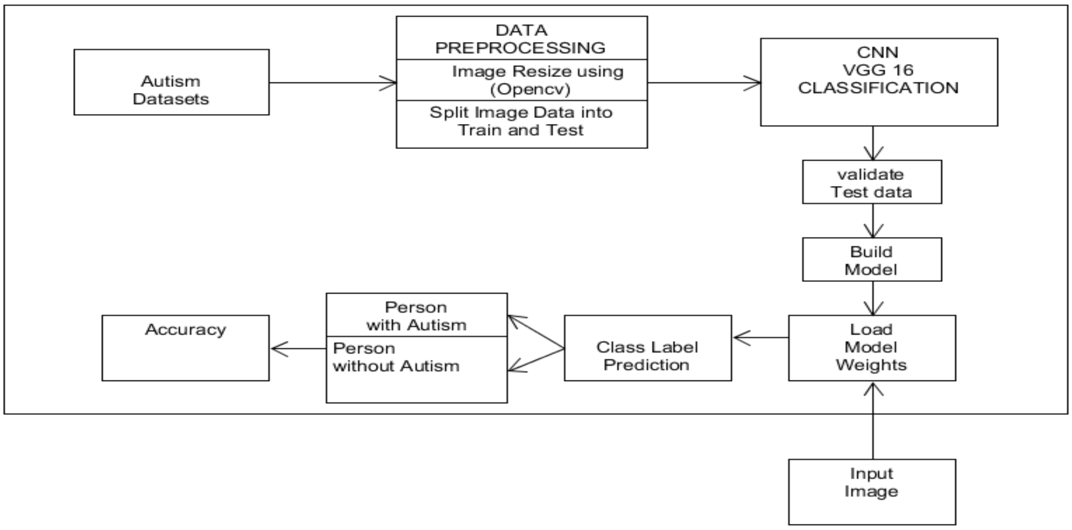

Fig. 2 System Model

Collection datasets

- In order to make the prediction, we will gather datasets.
- There are two classes in the data set.
  1.Typical Control
  2.Autism

Data Pre Processing

- On the selected data, we'll use a few image-pre-processing procedures as part of data pre-processing.
- Image Resize
- And Splitting data into train and test

Data Modeling

- The CNN VGG16 algorithm receives the split train data as input, which aids in training.
- The algorithm evaluated the learned brain imaging data after obtaining test data.
- Calculating accuracy.

Build Model

As part of data pre-processing, we'll apply a few image-pre-processing techniques to the chosen data.

V. RESULTS AND DISCUSSION

Experiments

We'll go over the experiments we conducted to evaluate the performance of the ensemble CNN technique for diagnosing ASDs in this part. The ABIDE dataset Using the resting state brain MRI data from the Autism Brain Imaging Data Exchange (ABIDE) dataset, we present our findings. The pre-processing may include motion correction, intensity normalisation, and slice-timing correction, depending on the pipeline being used. We used the same pre-processing approach (C-PAC) and atlases (Harvard-Oxford) as specified in to make comparisons as easy as possible. As a result, a dataset was created that included 872 of the original 1112 patients from 20 distinct sites. Classifying a patient as having either an ASD (autism spectrum disorder) or a Typical Control classification is the goal (TC). The goal is to categorise a patient as having either Typical Control or Autism Spectrum Disorder (ASD) (TC). The dataset and other pre-processing approaches are accessible through the nilearn Python module 2.

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TRAINING AND VALIDATION ACCURACY

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_1 (Rescaling)     (None, 64, 64, 3)         0

 conv2d (Conv2D)             (None, 64, 64, 16)        448

 max_pooling2d (MaxPooling2D  (None, 32, 32, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 16, 16, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 16, 16, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 8, 8, 64)         0
 2D)

 flatten (Flatten)           (None, 4096)              0

 dense (Dense)               (None, 128)               524416

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 548,258
Trainable params: 548,258
Non-trainable params: 0
```

The detected ultrasound component is scaled to 64 x 64 in height and breadth for training purposes. The input image is first convolutioned with 32 3X3 filters, yielding 10148 parameters. The activation function for this convolution is ReLU. To pool the convolution layer's 2-dimensional vector as much as possible, a 2X2 matrix is employed. The second convolution of the resulting data, which employs ReLU activation and 64 filters with a kernel size of 3X3 array, results in 51264 parameters. The maximum pooling filter size for this convolution is 2X2. In the second convolution, 51264 parameters are generated. Using a flattened layer, these 4164 data are transformed into a vector with a single dimension. The input vector is flattened and nonlinear operations are performed on it using 548,258 parameters in the first dense layer. The second dense layer's output is 128 parameters. In this study, sigmoid activation— due to the binary level disease categorization, which accepts single dimension data as input from a flattened layer.
This architecture creates 128 features from the input photos utilising metrics, loss, and learning rate algorithms. The model is trained using fit supplied architectural data. As seen below, the accuracy during training and validation is 99 percent on each occasion.

```
epochs=5
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/5
273/273 [==============================] - 78s 284ms/step - loss: 0.0392 - accuracy: 0.9908 - val_loss: 0.0023 - val_accuracy:
0.9995
Epoch 2/5
273/273 [==============================] - 42s 155ms/step - loss: 0.0048 - accuracy: 0.9997 - val_loss: 0.0012 - val_accuracy:
0.9995
Epoch 3/5
273/273 [==============================] - 43s 155ms/step - loss: 0.0028 - accuracy: 0.9997 - val_loss: 0.0024 - val_accuracy:
0.9995
Epoch 4/5
273/273 [==============================] - 42s 155ms/step - loss: 8.4163e-05 - accuracy: 1.0000 - val_loss: 0.0017 - val_accura
cy: 0.9995
Epoch 5/5
273/273 [==============================] - 43s 156ms/step - loss: 1.1698e-05 - accuracy: 1.0000 - val_loss: 0.0019 - val_accura
cy: 0.9995
```

VI. CONCLUSION

With the aid of deep learning techniques, this application aids in the prediction of the outcome for diagnosing the autistic disorder. People might not be able to identify autism by looking at brain scans. Artificial intelligence can identify it because it can locate and categorise brain images with delicate and detailed properties. Autism was detected in this work using the CNN-VGG16 algorithm. The proposed model has a 99.9% accuracy rate.

Future Enhancement
Although we used relatively low-quality photographs in this application, in the future we may use high resolution images and forecast the outcome using various techniques.

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REFERENCES

[1] Md Rishad Ahmed, Md Shale Ahammed, Deep Learning Approached Features for ASD Classification using SVM , 2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS).
[2] Dr. U B Mahadevaswamy, Autism Detection using machine learning, 22-sep-2021.
[3] Qaysar Mohi-ud-Din, A. K. Jayanthy, Detection of Autism Spectrum Disorder from EEG signals using pre-trained deep convolution neural networks, 2021 IEEE.
[4] Sakib mostafa , Lingkai tang, Diagnosis of Autism Spectrum Disorder Based on Eigenvalues of Brain Networks, September 20, 2019.
[5] B.Pugazhenthi, G.S.Senapathy, M.Pavithra, Identification of Autism in MR Brain Images Using Deep Learning Networks, IEEE 6th International Conference on smart structures and systems ICSSS 2019.
[6] Yuqing Song, Thomas Martial Epalle and Hu Lu, Characterizing and Predicting Autism Spectrum Disorder by Performing Resting-State Functional Network Community Pattern Analysis, 14-june-2019.
[7] Osman Altay, Mustafa Ulas, Prediction of the Autism Spectrum Disorder Diagnosis with Linear Discriminant Analysis Classifier and K-Nearest Neighbor in Children, IEEE-2018.
[8] Md. Fazle Rabbi, S. M. Mahedy Hasan, A Convolutional Neural Network Model for EarlyStage Detection of Autism Spectrum Disorder, 2021 IEEE
[9] Anibal Sólon Heinsfeld, Alexandre Rosa Franco, Identification of autism spectrum disorder using deep learning and the ABIDE dataset, 2017 Aug 30.
[10] Xia-an Bi, Yang Wang, Qing Shu, Classification of Autism Spectrum Disorder Using Random Support Vector Machine Cluster, 06 February 2018