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E-Mail

editor.ijmece@gmail.com

editor@ijmece.com

www.ijmece.com

Examination and Diagnosis of Autism Spectrum Disorder Using Deep Learning

Jella Badri

Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
badrijella02@gmail.com

B. Venugopal

Computer Science and Engineering(Data science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
venugoudboyapally@gmail.com

P. Venkatesh

Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
polojuvenkatesh25@gmail.com

T. Shravan Kumar

Assistant Professor

Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
shravankumart7@gmail.com

Abstract

Repetitive behaviors, limited interests, communication issues and trouble interacting with others are symptoms of autism spectrum disorder (ASD), a developmental and neurological illness that affects children's social and cognitive abilities. The intensity and duration of ASD symptoms may be mitigated with early diagnosis. A relatively new method that has the potential to aid in the early and accurate diagnosis of autism spectrum disorder (ASD) and the avoidance of its long-term repercussions is federated learning (FL). In this study, we see a first: the FL approach has been trained locally to classify ASD variables and diagnose ASD in both children and adults. The ML classifiers used are logistic regression and support vector machine. In order to find out which method is the most accurate in detecting ASD in adults and children, the outputs from various classifiers have been sent to a central server via FL, where a meta classifier is developed. We extracted characteristics from four separate ASD patient datasets, each of which had over 600 records of affected adults and children, sourced from various repositories. With a success rate of 81% in adults, median age, and 98% in children, the suggested model accurately predicted ASD is 91% accuracy. And provide safety measures

Keywords: ASD, ML, SVM, Logistic Regression, Deep learning.

Introduction

Children and adults alike are profoundly impacted by the social development-impairing symptoms of autism, a neuro-developmental condition. While there may not be a cure for autism spectrum disorder (ASD), early detection is better than traditional behavioral investigations, which take a long time to uncover and diagnose the disorder by analyzing children's behavior in clinics¹. Although most children with ASD are identified between the ages of 2 and 4, the age at which a diagnosis is made might vary according on the severity and complexity of the symptoms. Environmental circumstances or genetic links are the most common causes of this condition, which affects the neurological system and has far-reaching consequences for adults' and children's social and cognitive abilities. Its symptoms might range from mild to severe,

depending on the individual. Repetitive behaviors, fixation on certain topics, and trouble communicating in social settings are common symptoms of the disorder. Professionals in child healthcare and psychology must conduct a battery of tests to diagnose autism spectrum disorder (ASD). Getting autism spectrum disorder (ASD) diagnosed and treated early improves a person's quality of life by reducing the severity of symptoms. Unfortunately, because ASD cannot be accurately diagnosed by observing alone the behaviors of adults or children in a clinical setting, a significant amount of time might be wasted in the diagnostic process. Early detection of autism spectrum disorder (ASD) is achievable via a variety of clinical techniques; however, these diagnostic tests are labor-intensive and seldom performed unless the likelihood of ASD development is high. One possibility is to use machine learning (ML) to train ASD models more quickly and accurately. If we want to help families get to the life-saving treatments they need faster, we need ML approaches that can accurately and rapidly evaluate the risk of autism spectrum disorder (ASD) and streamline the whole diagnosis process. Early prediction of autism using various ML classification models may help avoid the long-term impacts of the disorder in both children and adults⁸. Hosseinzadeh et al.¹⁰ suggested an Internet of Things (IoT) based solution for autism spectrum disorder (ASD) identification, while Eslami and Saeed¹¹ offered a deep learning based model for the healthcare of patients affected by autism spectrum disorder (ASD). Among the many additional computational strategies suggested in literature⁹ are many more. Nevertheless, whether in a centralized or distributed

setting, it remained difficult to acquire massive amounts of data for the purpose of training models. Data are the most precious asset for hospitals, thus they are hesitant to share them. Additionally, regional data protection laws ban data sharing¹². Concerns about data privacy, security, and protection are significant for data owner companies. There are additional challenges, such as data theft¹³, connection delays, and network slowness, when transmitting large datasets across the network to train machine learning models. Hence, a model should be suggested where data stays secure with the owner organization; this is an extremely pressing need.

Literature Survey

Repetitive behaviors and difficulties with social interaction and communication are hallmarks of Autism Spectrum Disorder (ASD), a neurodevelopmental disorder. In a number of contexts, deep neural networks have shown to be quite effective. Using a convolutional neural network (CNN) using the ResNet-50 architecture is one way to find children at risk of autism spectrum disorder (ASD) early on. This approach has shown good results in terms of sensitivity and specificity by analyzing photographs of persons with ASD and normal controls. Graph convolutional networks (GCNs) applied directly to a population-averaged brain network and self-attention graph pooling are the building blocks of a new ASD prediction model, as described in another paper. After training, this model readily outperforms current models on the ABIDE-I database and may be used to diagnose new cases. The scant neurobiological evidence and complicated psychological symptoms of ASD make diagnosis difficult. The strategic and structural components of ASD have, however, been studied using deep learning models, such as recurrent neural networks and convolutional neural networks. Researchers have been able to

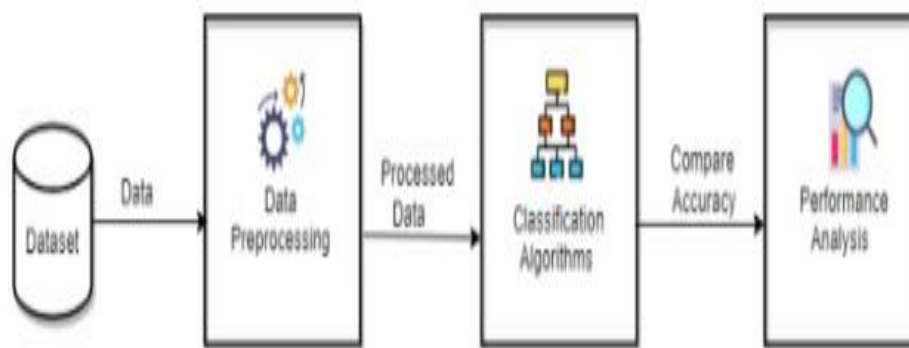
see combinations of brain regions that are very suggestive of the categorization process by training 3D convolutional neural networks. Also, sequences of brain areas may now be effectively classified using recurrent neural networks. Important subcortical regions, such as the basal ganglia (BG), are involved in ASD characterization, and this study has uncovered important strategic and anatomical evidence related to these areas. The dearth of autism spectrum disorder (ASD) experts in rural regions makes it challenging to properly detect and screen youngsters, despite the critical need of early diagnosis. Several methods have been devised to assess the efficacy of ASD treatments and to detect ASD in its early phases.

In the 2019 Saliency for ASD Challenge, a dataset containing scans of 300 children with or without ASD was released to benchmark saliency prediction for ASD and classification algorithms. Deep learning has shown impressive performance in computer vision and image analysis applications. A proposed approach for ASD classification involves using convolutional neural networks (CNNs). The CNNs were initially introduced by LeCun et al. in 1989 and were successfully applied to identify handwritten zip code digits for the US Postal Service. It was discovered that CNNs can directly handle large amounts of low-level information, surpassing traditional pattern

analysis and classification methods. However, due to limitations in computing power, CNNs were not widely used until two decades later. The advent of powerful GPUs (Graphics Processing Units) in 2006, implemented by Chellapilla et al., significantly accelerated CNN computations. Various improvements have been made to the original CNN algorithm, including the introduction of max pooling by Huang et al. in 2007. In 2012, Alex Krizhevsky et al. revolutionised large-scale image recognition with deep convolutional neural networks, achieving highly accurate results on the ImageNet dataset. Since then, deep convolutional neural networks have been successfully applied in various fields

Methodology

In the proposed architecture, Federated learning process starts from step three in which pre-processed and normalized datasets have been processed for training of SVM and LR classifiers. Workflow of FL process is presented. Results of these classifiers in terms of accuracy, precision and F1 score have been calculated and transmitted to central server for training of meta classifier at server. Meta classifier will determine which model is more appropriate in detecting autism and will train the global model accordingly. Global model will be disseminated in all clients as a single tool for autism detection.



Proposed diagram

The children, median, and adult datasets presented in have been divided into training and test datasets. Training datasets contained 80% records and testing datasets which will be used to test the proposed model contained 20% of total records.

The response dataset contained some noisy and missing records therefore data transformations were needed to carry out prior to train ML classifier for model training and analysis. Category variables are handled using label encoding. To make labels machine-readable, label encoding transforms them into numeric form. Repeated labels receive the same value as those that were previously allocated. The binary label encoding of classes with ten features have been chosen.

Results obtained after training local models have been transmitted to central server through 4G ethernet gateway where meta classifier is trained to predict which ML model is outperforming in prediction of ASD. Best model is selected for the training of global model that is transmitted back to the clients so that all clients use same efficient model for autism detection.

Collection of datasets

- We will acquire datasets from Kaggle.com to use for prediction.
- The datasets consist of two classes: 'Normal' and 'Autism'

Data Pre-Processing

- In the data pre-processing phase, we will apply various image pre-processing techniques to the selected data.
- The trained data related to autism will be evaluated by using the algorithm with the test data, and accuracy will be calculated.

Data Modelling

The split training data will serve as input for the logistic regression, and SVM algorithms, which will facilitate the training process.

- The trained data related to autism will be evaluated by using the algorithm with the test data, and accuracy will be calculated.

Validation

In response set, data points have been gathered into one of the following four classes to validate ASD diagnosis. Class1: true positive (TP) indicates that the person has autism, and we have correctly recorded autism positivity. Class 2: true negative (TN) means that a person does not has autism and wrongly recorded as negative in response dataset. Class 3: false positive (FP) depicts that response dataset incorrectly recorded that a person had ASD who does not have it. Class 4: false negative (FN) indicates that it was predicted mistakenly that the person does not have ASD, but they have ASD. The confusion matrix of ASD that facilitated in the validation process

Precision, recall and F1 score are the measures used to validate performance of LR and SVM classifiers. Precision demonstrates the cases that detected autism and we predicted them correctly.

RESULTS

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Autism Spectrum Disorder Decision Support Tool

This is a web-based integrative machine learning framework that predicts risk to autism spectrum disorder using prenatal drug exposures. The data is extracted from electronic medical records from a single Israeli Health Maintenance Organization. The trained machine learning model is made available to predict autism risk. The model is 71%(approx) accurate.

Instruction: Fill the form with input counts of medications taken from mother-father to predict whether a child will be at risk of autism, where .y denotes mother and .x denotes father.

Instructions: Please fill in this form with the count of each drugs taken within the last 10 years.

Cardiovascular system: Beta-blocking agents (C02C.x)

Anterior Pituitary Lobe Hormones (H01A.x)

Psychoanaleptic, psychostimulants, agents used for ADHD and nootropics (N06B.x)

Various, other diagnostic agents (V04C.x)

Alimentary tract and metabolism: antidiarrheals, intestinal, anti-inflammatory/anti-infective agents (A07B.y)

Blood/Blood-forming-organ: Antihemorrhagic drugs; Vitamin K and other hemostatics (B02B.y)

Blood/Blood-forming-organ: Antianemic drugs, Vitamin B12 and folic acid (B03B.y)

Blood/Blood-forming-organ: Blood substitutes and perfusion solutions: irrigating solutions (B05C.y)

Home page

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Blood/Blood-forming-organ: Antianemic drugs, Vitamin B12 and folic acid (B03B.y)

Blood/Blood-forming-organ: Blood substitutes and perfusion solutions: irrigating solutions (B05C.y)

Cardiovascular System: Cardiac therapy, cardiac stimulants excluding cardiac glycosides (C01C.y)

Anti-infective for systemic use: Immune sera and immunoglobulins (J06B.y)

Nervous system: analgesic drugs; other analgesics and antipyretics (N02B.y)

Sensory Drugs: Otologicals (S02D)

Cardiovascular system: cardiac therapy; class 1 and class 3 antiarrhythmic drugs (C01B.y)

Sensory drugs: Ophthalmological drugs, mydriatics and cycloplegics (S01F.y)

Alimentary tract and metabolism: drugs for functional GI disorders, antispasmodics in combination with analgesics (A03D.y)

Nervous system: Antiparkinson drugs; dopaminergic agents (N04B.y)

Nervous system: Analgesic drugs: migraine medication (N02C.y)

Musculoskeletal system: drugs for treatment of bone disease/ drugs affecting bone structure and mineralization (M05B.y)

Genito/urinary system: sex hormones (G03F.y)

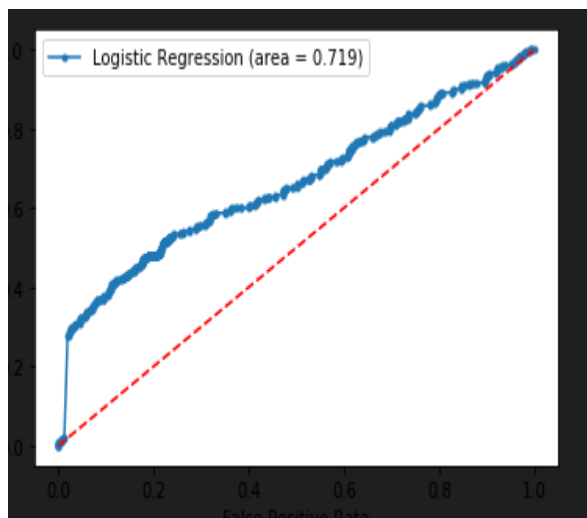
Submit

Input image

Autism Risk Analysis

According to our machine learning model, the child is at low risk for autism.

Prediction



Graph

Conclusion

The assessment of ASD has been associated with multiple disorders recognized as features including, behavioural, emotional, structural and mental disorders that make it difficult to predict due to non-availability of medical tests for all

features needed to detect ASD in a person. Practitioners diagnose ASD in patients by using psychological assessments and response observation. Detection process is time-consuming and complex as symptoms are not obvious. Presently, there is no screening method that has been optimized and thoroughly developed to specifically detect the ASD, nor is there a screening test that can accurately diagnose ASD. ML is the most recent development that can facilitate in predicting autism more accurately saving lots of time. ML can be helpful in early diagnosis of ASD in patients of all ages including children and adults. In this work, we have applied two different ML models (SVM, LR) on the dataset containing features of children and adults. It was observed that SVM showed 81% accuracy in detecting ASD in adults and LR gave 91% accuracy in determining ASD in children. In future, different transfer-learning models i.e. logistic regression can also be used in ASD detection using images dataset of autistic children for early detection of ASD with improved accuracy. Moreover, severity of disorder can also be measured through deep learning methods in future.

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