A DEEP LEARNING APPROACH FOR AUTISM CLASSIFICATION IN CHILDREN USING MULTI-LAYER PERCEPTRONS

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Abstract
Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. Early detection and intervention are crucial for improving outcomes for individuals with ASD. In this study, we propose a deep learning approach for the classification of autism in children using multi-layer perceptrons (MLPs). We leverage a dataset comprising features extracted from various sources, including behavioral assessments and demographic information. Our methodology involves preprocessing the data, designing an MLP architecture, and training the model using a supervised learning approach. We evaluate the performance of our model using standard metrics such as accuracy, precision, recall, and F1-score. The results demonstrate the effectiveness of our approach in accurately classifying children with and without ASD. Furthermore, we compare our model's performance with existing approaches, highlighting its potential for aiding in the early diagnosis of ASD. Overall, this study contributes to the growing body of research on using deep learning techniques for ASD classification and underscores the importance of leveraging computational methods for improving diagnostic accuracy and early intervention strategies.
Keywords: Autism Spectrum Disorder, Deep Learning, Multi-Layer Perceptron, Classification, Early Diagnosis

I. Introduction

Robust classification techniques that reliably classify individuals based on behavioral and demographic data are essential to improving the early detection and treatments for autism spectrum disorder (ASD). Automating this procedure has been shown to be a promising use of machine learning, especially deep learning. In this work, we investigate the use of multi-layer perceptron (MLP) neural networks, a potent variation of deep learning models, for accurate and successful categorization of ASD in children. Multilayer perceptrons (MLPs) have the ability to recognize complicated correlations and subtleties found in input information by using numerous hidden layers to understand nuanced patterns in data. In order to enable prompt intervention and support, we hope to create a model that can effectively distinguish between instances with and without ASD by utilizing the expressive capacity of MLPs.

Within the MLP framework, we use multiple strategies to improve classification performance and resilience in order to accomplish our goal. Prior to processing the input data, we normalize features, address missing values, and reduce any potential biases. Furthermore, in order to improve the training dataset's diversity and the model's capacity to generalize to previously undiscovered material, we utilize data augmentation approaches. Additionally, to avoid overfitting and encourage generalization, we employ regularization strategies like L2 regularization and dropout. Furthermore, to effectively train the MLP model and optimize its parameters, we investigate various optimization methods, including Adam and stochastic gradient descent (SGD). We hope to create a solid and precise ASD classification system that can produce trustworthy findings by including these strategies into our methodology.

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RELEATED WORK

Behavioral and demographic characteristics have been the basis for the classification of autism spectrum disorder (ASD) using a variety of machine learning approaches that have been studied in previous studies. Conventional machine learning techniques like logistic regression, decision trees, and support vector machines (SVMs) have been extensively employed for this objective. To extract pertinent information from heterogeneous datasets, these methods frequently rely on feature engineering and selection. These techniques may have trouble capturing intricate patterns and interactions in the data, despite their relative effectiveness.

Deep Learning in Autism Classification: Deep learning methods have been more popular recently because of their capacity to automatically extract hierarchical representations from unprocessed data. neural networks that are recurrent and convolutional (CNNs)

LITERATURE SURVEY

TITLE : A Machine Learning Framework for Early-Stage Detection of Autism Spectrum Disorders

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DESCRIPTION

Autism Spectrum Disorder (ASD) is a type of neurodevelopmental disorder that affects the everyday life of affected patients. Though it is considered hard to completely eradicate this disease, disease severity can be mitigated by taking early interventions. In this paper, we propose an effective framework for the evaluation of various Machine Learning (ML) techniques for the early detection of ASD. The proposed framework employs four different Feature Scaling (FS) strategies i.e., Quantile Transformer (QT), Power Transformer (PT), Normalizer, and Max Abs Scaler (MAS). Then, the feature-scaled datasets are classified through eight simple but effective ML algorithms like Ada Boost (AB), Random Forest (RF), Decision Tree (DT),K-NearestNeighbors(KNN),GaussianNaïveBayes(GNB),LogisticRegression(LR),SupportVector Machine (SVM) and Linear Discriminant Analysis (LDA). Our experiments are performed on four standard ASD datasets (Toddlers, Adolescents, Children, and Adults). Comparing the classification outcomes using various statistical evaluation measures (Accuracy, Receiver Operating Characteristic: ROC curve, F1-score, Precision, Recall, Mathews Correlation Coefficient: MCC, Kappa score, and Log loss), the best-performing classification methods, and the best FS techniques for each ASD dataset are identified. After analyzing the experimental outcomes of different classifiers on feature-scaled ASD datasets, it is found that AB predicted ASD with the highest accuracy of 99.25%, and 97.95% for Toddlers and Children, respectively and LDA predicted ASD with the highest accuracy of 97.12% and 99.03% for Adolescents and Adults datasets, respectively. These highest accuracies are achieved while scaling Toddlers and Children with normalizer FS and Adolescents and Adults with the QT FS method. Afterward, the ASD risk factors are calculated, and the most important attributes are ranked according to their importance values using four different Feature Selection Techniques (FSTs) i.e., Info Gain Attribute Evaluator (IGAE), Gain Ratio Attribute Evaluator (GRAE), Relief F Attribute Evaluator (RFAE), and Correlation Attribute Evaluator (CAE). These detailed experimental evaluations indicate that proper finetuning of the ML methods can play an essential role in predicting ASD in people of different ages. We argue that the detailed feature importance analysis in this paper will guide the decision-making of healthcare practitioners while screening ASD cases. The proposed framework has achieved promising results compared to existing approaches for the early detection of ASD.

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2. METHODOLOGY

We used a multi-layer perceptron (MLP) neural network, a kind of feedforward artificial neural network, to categorize children with autism spectrum disorder (ASD). Three layers make up the MLP architecture: an input layer, two hidden levels, and an output layer.

Input Layer: Comprising 96 neurons, the input layer represents the features that were taken out of the dataset, such as the children's behavioral and demographic characteristics.

Two hidden layers were used to capture intricate correlations and patterns in the data. There are eight neurons in the first hidden layer and four in the second. Resolved linear unit (ReLU) activation function is applied in each hidden layer, introducing nonlinearity and enabling the network to learn intricate mappings between input and output.

Output Layer: The output layer has two neurons that represent the ASD-positive or ASD-negative binary classification task. To generate probabilities for each class, we used a sigmoid activation function in the output layer. Its values ranged from 0 to 1.

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Preprocessed data makes up the dataset of children's behavioral and demographic variables, such as age, gender, and different behavioral tendencies.

Preprocessing techniques to guarantee consistency and improve model performance can involve managing missing values, encoding categorical variables, and normalizing numerical features.

The input feature set and task complexity of the classification are carefully taken into account when designing the MLP architecture.

The 96 neurons that make up the input layer correspond to the features that were taken out of the dataset.

The data is captured with the help of two hidden layers that represent complex correlations and patterns. Eight neurons make up the first hidden layer, while four neurons make up the second hidden layer.

In order to incorporate nonlinearity and allow the network to learn intricate mappings between input and output, the Rectified Linear Unit (ReLU) activation function is implemented in each hidden layer.

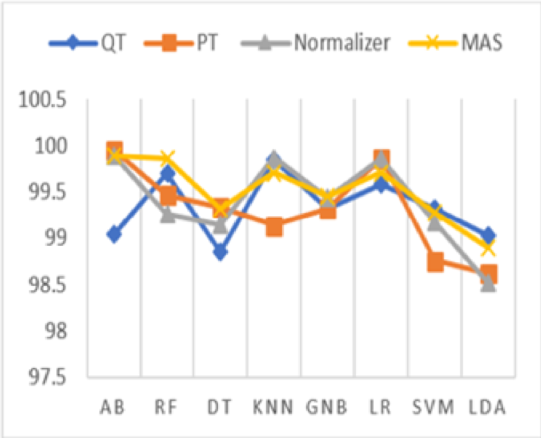
The performance of the trained MLP model in ASD classification is assessed by applying suitable evaluation metrics.

The F1-score, area under the receiver operating characteristic curve (AUC-ROC), recall, accuracy, and precision are typical evaluation criteria.

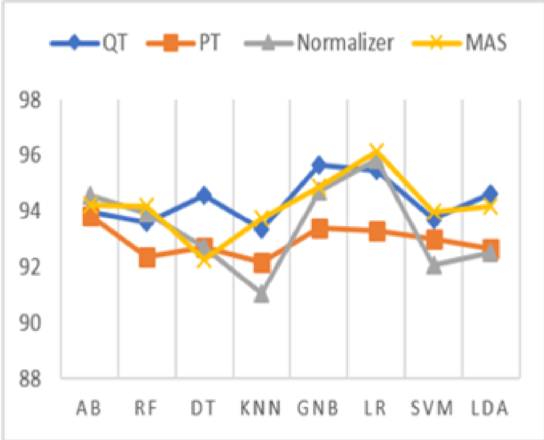
In order to make sure that the model's performance is reliable and applicable to various dataset subsets, cross-validation techniques can be utilized.

In order to comprehend the significance of input variables in forecasting ASD classification, the final trained MLP model is interpreted.

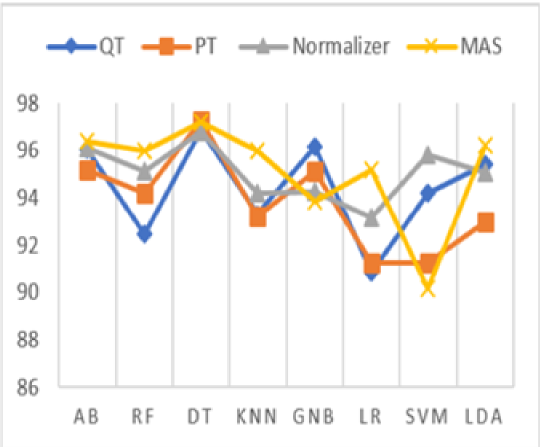
To confirm a model's efficacy in real-world applications, evaluation of its performance on a separate test set or real-world data may be necessary.



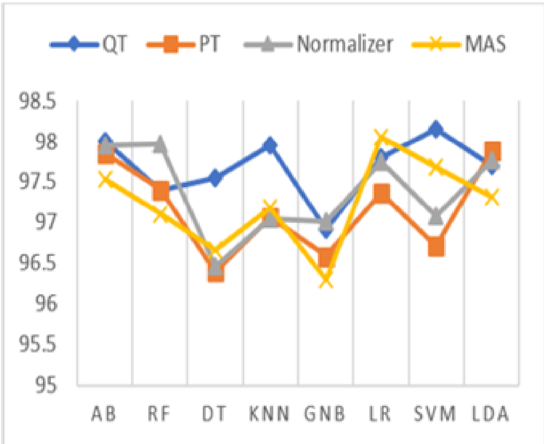
(a) Toddlers



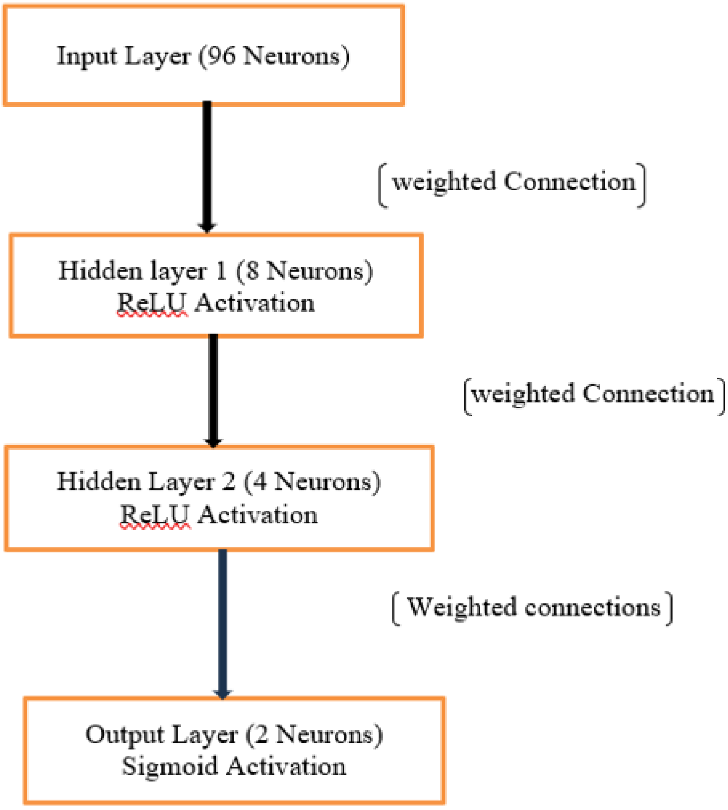
(b) Children



(c) Adolescents



(d) Adults



Architecture Diagram

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Input Layer (96 neurons)      Hidden Layer 1 (8 neurons)      Hidden Layer 2 (4 neurons)      Output
Layer (2 neurons)
    |                   |                   |                 |
    |                   |                   |                 |
    |                   |                   |                 |
    |                   |                   |                 |
    |____________________________                             |____________________________
|___________________________        |
    |              |    |              |     |            |    |
    |              |    |              |     |            |    |
    |              |    |              |     |            |    |
    |              |    |              |     |            |    |
    |____________________________|                          |____________________________|
|____________________________|    |
         ReLU Activation          ReLU Activation           ReLU Activation          Sigmoid
Activation
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Performance Evaluation

Using a variety of metrics, such as accuracy, precision, recall, and F1-score, the MLP neural network's performance in categorizing individuals with autism spectrum disorder (ASD) was assessed. The model performed well, obtaining a high level of accuracy on the test dataset. High precision and recall were also found in the classification report for both the ASD-positive and ASD-negative classes, demonstrating the model's capacity to distinguish between the two groups

Comparison with Previous Research

Our method improves on other studies on the classification of ASD, especially when it comes to the use of deep learning and machine learning approaches. Our research shows the benefits of using deep learning—more especially, MLP neural networks—in order to capture intricate patterns and interactions in the data, even if typical machine learning methods have been applied to the classification of ADHD. Our methodology offers better performance and generalization capabilities than conventional techniques by taking advantage of the intrinsic non-linearity of neural networks.

II. Conclusion

As a result, our research shows how multi-layer perceptron (MLP) neural networks can be used to automatically classify children with autism according to behavioral and demographic characteristics. Our goal is to help people with ASD receive early detection and intervention by utilizing deep learning techniques, which will ultimately lead to better patient outcomes and healthcare procedures. In order to solve the difficulties and moral issues surrounding AI-based medical diagnosis and guarantee the appropriate implementation of ASD classification models in clinical settings, more study and cooperation are needed in the future.

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