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DEEP LEARNING (DL) BASED IMPROVED PROBABILISTIC DENSE MODEL (IPD) FOR AUTISM SPECTRUM DISORDERS (ASD) CLASSIFICATION ANALYSIS

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ABSTRACT

Among other symptoms, people with autism spectrum disorder (ASD) suffer from communication, social interaction, and repetitive habits. Even while complete eradication is not common, early interventions may make the illness more manageable. Here, we propose a practical framework for contrasting various Machine Learning (ML) methods for diagnosing ASD at an early age. The proposed framework uses a number of Feature Scaling (FS) methodologies, such as min-max scalar, principal component analysis, and intuitive visual representation analysis, to incorporate an efficient prediction method into the overall architecture. Our recommended design, which utilizes the IPD model, suggests that the categorization of adult autism spectrum condition, as an entity, is reflected in the overall verification of the features, and varied functional qualities. To do the mathematical analysis in our IPD model, we use chi-squared and probability density functional methods. The structure's purpose is to recognize and classify patients based on their palpable traits. We can observe that the 95.9% accuracy is far greater than the Machine Learning approach in the end.

Keywords: improved probabilistic dense model (IPD), artificial neural network (ANN), random forest classifier, support vector machine (SVM), confusion matrix (CM), ensemble approach (EA).

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INTRODUCTION

ASD, a neurodevelopmental disease, affects a person's ability to form relationships with others and has interpersonal problems from an early age [1-2]. The broad range of symptoms and intensity exhibited in people with ASD are referred to as the "spectrum" [3-5]. Although there is no known treatment for ASD, research has shown that early intervention and medical care may significantly enhance a child's development by assisting them in developing socially acceptable behaviors and productive communication techniques [6-8]. However, it can be very difficult and subtle to identify and diagnose ASD using traditional behavioral studies. Between the ages of two and three, an autism diagnosis is frequently given, depending on the severity of the symptoms [9-11]. There are numerous ways to diagnose autism spectrum disease at an early age [1-2]. These diagnostic methods are typically not widely used, even when there is a substantial possibility that a child may develop an autism spectrum condition. A succinct, observable checklist covering early life, childhood, adolescence, and adulthood was provided by the authors in [12]. The AS Tests mobile applications method for quick ASD screening was subsequently developed by the authors in [13] based on a variety of surveys and questionnaires, including the AQ-10 and the Q- CHAT. To encourage more study in this area, they created a publicly accessible dataset utilizing information from mobile applications and published it on two websites, the UCI machine learning repository and Kaggle. Different Machine Learning (ML) approaches have been utilized in various studies over the past few years to quickly and accurately identify ASD and other illnesses such as diabetes, stroke, and heart failure [14-16]. The authors of [17] examined ASD characteristics using rule-based machine learning (RML) techniques and discovered that RML helps classification models by increasing classification accuracy. In [18], the authors used the Random Forest (RF) and Iterative Dichotomies 3 (ID3) algorithms to produce prediction models for children, adolescents, and adults. [19] Addresses the issues of data inadequacy, non-linearity, and inconsistency by introducing a novel evaluation tool that combines ADI-R and ADOS ML procedures and employs a number of attribute encoding techniques. In another study by the authors [13], which uses cognitive computing to disclose a correlation value between characteristics and classes, Support Vector Machines (SVM), Decision Trees (DT), and Logistic Regression (LR) were utilized as ASD diagnostic and prognostic classifiers. A correlation-based attribute selection method was also used in [20] to determine the importance of the traits in both cases of traditionally formed (TD)
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MATERIAL AND METHODS

With the dataset acquisition based on the gender types and the importance of the autism type, we have used the various features as described below in this section. This section includes information about the many dataset features, such as the block diagram, algorithm, and IPD model that show the total estimated loss characteristics as listed below.

Dataset Description

The dataset, which was gathered from the Kaggle website, shows how the features fluctuate generally depending on the type of autism or the person's autism relevance. In order to build the overall class labels with AUTISM and NO - AUTISM, these features are used in conjunction with the unbalancing of the data indicating the SMOTE feature of the design. In Figure-1, we have mentioned the entire dataset properties and functionalities.

Feature	Description
index	The participant's ID number
AX_Score	Score based on the Autism Spectrum Quotient (AQ) 10 item screening tool AQ-10
age	Age in years
gender	Male or Female
ethnicity	Ethnicities in text form
jaundice	Whether or not the participant was born with jaundice?
autism	Whether or not anyone in tbe immediate family has been diagnosed with autism?
country_of_res	Countries in text format
used_app_before	Whether the participant has used a screening app
result	Score from the AQ-10 screening tool
age_desc	Age as categorical
relation	Relation of person who completed the test
Class/ASD	Participant classification

Figure-1. Representing dataset description.

The figure shows the overall block diagram of the proposed IPD model. In Sections 2.c and 2.d, the proposed IPD method and related loss formulations are successfully applied. According to the IPD algorithm and its formulations, the initial design process is shown in Figure-2 with an effective weight parametric. The specific probability matching of the features that are effectively estimated with multi objective functionalities in the dataset. Hence these feature relates the overall validation accuracy to be more precise and better for every iteration. The overall loss is estimated with custom function with log loss on the expected probabilities for each feature affecting Autism.

Algorithm for IPDM (Improved Probabilistic Dense Model)

Input: Let X be the overall cleaned data, X_{cm},$_{mp}$,X_{Fc},X_a are the layer input responses for the design flow

Output: Y be the final outcome of the IDDM+CNNfilter.

Procedure: CNN approach:

For i=1: M do

$X_{cm}=interpolate\_li(Z_i)$

$X_{mp}=resize\ (X_{cm},[a,b])$

$$X_{fc}=\sum\nolimits^{N}_{j=1} X_{cm}*w_{n+1}+X_{mp}*(k) \tag{1}$$

$X_a=X_{fc}*F_m(i)$

End loop

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$$\text{Model1} = \{X, X_{\text{mp}}, X_{\text{Fc}}, X_{\text{a}}\} \tag{2}$$

End Procedure

Loss Estimation

Since we are aware of a loss, the predicted speed for a particular circuit is determined using the conditional expected probability method, which is dictated by (1) and (2):

$$\left(\frac{X}{Y}\right) = (X) * \frac{P(X\cap Y)}{P(Y)} \tag{3}$$

Considering the previously indicated P(X) = chance of addressing the data for each iteration. If both the Time and data acquisition are linearly addressed, the conditional feature with probability on the data addressing with expected time is shown as:

E (X U T) = E(X) + E(T). A nonlinear technique is appropriate for the proposed design because the data is variable and the time will change with each repetition. Hence,

$$(X\cap T)=(X)+e^{E(T)} \tag{4}$$

Similarly for Y we have,

$$(Y\cap T)=(Y)+e^{E(T)} \tag{5}$$

Finally overall expected Probability with higher speed variant is:

$$\left(\frac{X}{Y}\right) = (X) * \frac{E(X\cap T)-E(Y)}{E(Y)} * \frac{E(Y\cap T)}{E(X)} \tag{6}$$

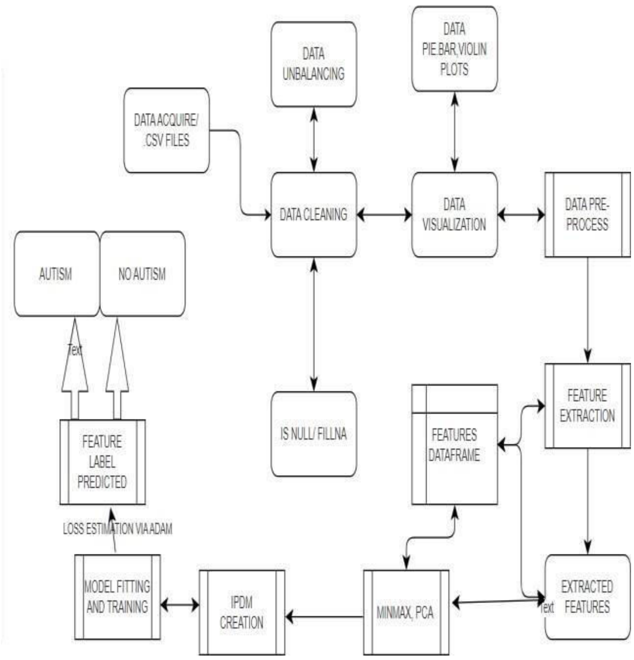

Figure-2. Representing the overall block diagram for autism classification using Deep learning model.

RESULTS AND DISCUSSIONS

The experimental model's behavior when compared to the suggested model shows the general design aspects that are lacking, as well as loss graphs and an accurate feature visualization and analysis.

A. Experimental Setup

We apply the dataset to local directories while innovating the general characteristics of autism and presenting various analysis results using algorithms, as shown in Table-1. Figure-3 tabulates the visual graphs with various components of the analysis section that are effectively sorted with various scores.

B. Data Analysis and Visualization

	Missing Values
A1_Score	0
A2_Score	0
A3_Score	0
A4_Score	0
A5_Score	0
A6_Score	0
A7_Score	0
A8_Score	0
A9_Score	0
A10_Score	0
age	2
gender	0
ethnicity	0
jundice	0
austim	0
contry_of_res	0
used_app_before	0
result	0
age_desc	0
relation	0

Figure-3. Representing the overall score for each type of autism features.

C. Analysis on Accuracy

The classification metric's overall accuracy was recorded in Table-1 along with the results of its implementation, which showed that it outperformed other techniques.

	precision	recall	f1-score	support
0	0.95	0.96	0.96	132
1	0.88	0.86	0.87	44
accuracy			0.94	176
macro avg	0.92	0.91	0.92	176
weighted avg	0.94	0.94	0.94	176

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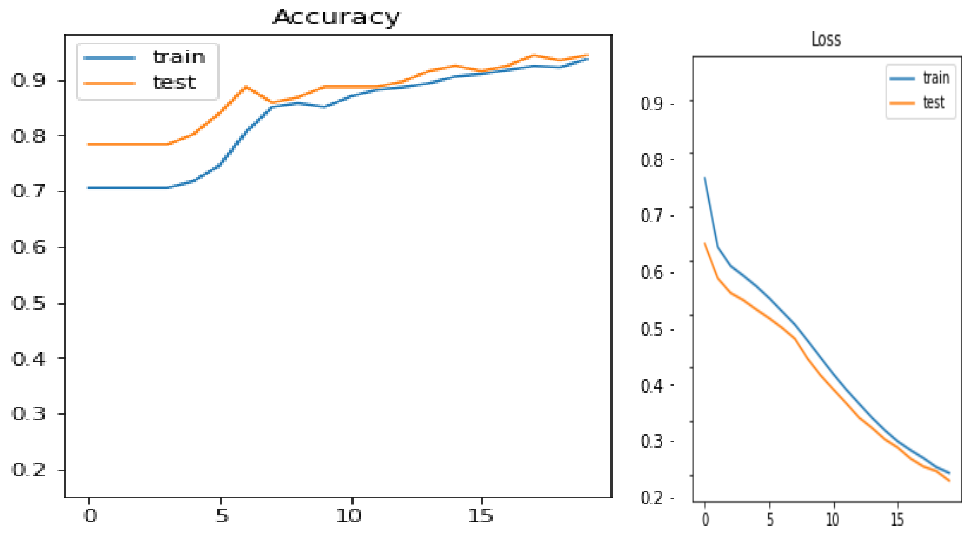

Figure-4. Representing the overall Training and Training loss and Accuracy.

The above graph shows the overall accuracy for training and testing up to 95%, which represents the greatest accuracy available from the machine learning algorithms currently in use. Despite the fact that the loss is significantly less when compared to other methods.

D. Tabulations

The representation of existing methods with the proposed algorithm (IPD) is shown below in Table-1, along with values for accuracy, sensitivity, specificity, F1-Score, recall, and precision.

Table-1.

ALGORITHMS	ACCURACY	SENSIVITY	SPECIFICITY	F1-SCORE	RECALL	PRECISION
LR[10]	74.3	52.86	47.43	78.8	81	76.7
RFC[7]	82.5	80.3	84.65	85.6	87.2	84.6
ANN[23]	89.56	92.01	91.23	86.3	87.4	85.3
KNN[5]	73.78	63.3	36.7	87.5	99.2	78.2
IPDM	93.75	96	98	96.0	96.0	95

CONCLUSION AND SCOPE:

Here the presented DL-based prediction models can be used as an alternative or perhaps as a useful tool by doctors to correctly diagnose ASD cases in patients of various ages. Additionally, the feature importance values were calculated using 95% prediction accuracy to determine the most important aspects for ASD prediction. These results are observed and supported by the study we propose.

Scope:

To achieve the entire dataset pruning and testing effectiveness based on the Long Short-Term Memory (LSTM) and other Service-Oriented Architecture (SOA) designs, many efficient features with more than 50 are to be developed.

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