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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: Individuals with Autism Spectrum Disorder (ASD) struggle with social interaction, communication, and repetitive behaviors, among other symptoms. Although total eradication is unlikely, early therapies may lessen the severity of the condition. In this study, we present a useful framework for comparing several Machine Learning (ML) approaches to ASD diagnosis at an early age. The suggested framework incorporates an effective prediction method into the overall design by using a variety of Feature Scaling (FS) techniques, including minmax scalar, principal component analysis, and intuitive visual representation analysis. Our suggested design using the IPD model shows that the overall verification of the features, various functional qualities reflects the adult autism spectrum disorder categorization in its entirety. In our IPD model, we use a chi-squared and probability density functional hybrid to do the mathematical analysis. The structure is meant to identify and categorize patients according to their observable characteristics. At the end of the day, we can see that the 95.9% accuracy is far higher than the Machine Learning method.
Keywords: Improved Probabilistic Dense Model (IPD), Artificial Neural Network (ANN), Random Forest classifier, Support Vector Machine (SVM), Logistic Regression, Confusion Matrix (CM), Ensemble Approach (EA).

INTRODUCTION

Autism spectrum disorder (ASD) is a neuro developmental disorder that influences a person's social connections and interpersonal difficulties from a young age. [1],[2].
The term "spectrum" is used to describe the vast variety of symptoms and severity seen in people with ASD [3, 4, 5]. There is currently no cure for ASD, however research has shown that early intervention and medical treatment may greatly improve a child's development by helping them learn socially appropriate behaviors and effective communication strategies [6, 7, 8]. However, the identification and diagnosis of ASD using conventional behavioral research are very challenging and nuanced. Depending on the severity of the symptoms [9], [10], [11], an autism diagnosis is often made between the ages of two and three. Many methods exist for early diagnosis of autism spectrum disorder. Even when there is a high likelihood that a child may acquire autism spectrum disorder, these diagnostic tools are not usually extensively employed. The authors in [12] presented a brief, observable checklist that spans infancy, childhood, adolescence, and adulthood. The authors in [13] then developed the AS Tests mobile applications system for rapid ASD detection based on a battery of questionnaires and

surveys, including the Q-CHAT and the AQ-10. As a result, they developed a publicly available dataset using data from mobile applications and uploaded it to two websites, the UCI machine learning repository and Kaggle, to spur more research in this direction. Several research in the last several years have used different Machine Learning (ML) methodologies to rapidly and accurately identify ASD and other disorders including diabetes, stroke, and heart failure [14, 15], [16]. Rule-based machine learning (RML) approaches were used to analyze ASD characteristics by the authors of [17], who found that RML aids classification models in improving classification accuracy.

In [18], the authors created prediction models for kids, teens, and adults by combining the Random Forest (RF) and Iterative Dichotomiser 3 (ID3) algorithms. Data insufficiency, non-linearity, and inconsistency are addressed in [19] by the introduction of a new assessment tool that integrates ADI-R and ADOS ML methodologies and implements several attribute encoding approaches. Support Vector Machines (SVM), Decision Trees (DT), and Logistic Regression (LR) were used as ASD diagnostic and prognostic classifiers in another work by the authors [13], which reveals a correlation value between features and classes using cognitive computing. Furthermore, in [20], a correlation-based attribute selection was utilised to establish the significance of the qualities in both conventionally formed (TD) (N = 19) and ASD (N = 11) instances. The authors of [21], who studied ASD and TD children in preschool, were able to identify 15 cases of ASD with only seven characteristics. They also said that cluster analysis might be used to successfully analyze complicated patterns in order to predict phenotypic and diversity in ASD. K-Nearest Neighbors (KNN), Linear Regression (LR), Linear Discriminant Analysis (LDA), Classification and Regression Trees (CART), Naive Bayes (NB), and Support Vector Machines (SVM) were compared for their classifier performance in predicting adult ASD by the authors of [22]. Using just one dataset and little comparison, the authors of [23] presented an ML model for autism identification by inducing rules. Another example of insufficient validation and comparison is shown in [17], where LR analysis was utilized to construct an ML autism classification strategy.

This study gathers different features of the design implicating the overall perspective of the classification model with patients or adults with autism or not. The scaling approach based on min-max model indicates the overall features, with the probabilistic features indicating the different responses based on the features that would govern the overall design perspective for the implementations. The autism classification for the proposed IPD model has the utmost efficiency from the existing algorithms (ML).

In this paper, our works aim to provide an improved model with probabilistic approach for Dense layers indicating overall performance characteristics for the research gaps observed in section-1. This section covers the overall perspective of the design algorithms that researchers have published and realized in real time developments. The section -2 provides the concept of proposed model indicating the overall block diagram, algorithm and loss estimation. While the section-3 implicates the results observed for the proposed with confusion and loss-accuracy plots. The overall performance metrics are tabulated and concluded accordingly.

MATERIAL AND METHODS

In this section we have utilized the different features as mentioned below with the dataset acquisition depending on the type of autism and its relevance based on the gender types. This section comprises on the different features of the dataset, including the block diagram, algorithm with IPD model indicating the overall estimated loss characteristics as mentioned below.

Dataset description

The dataset was taken from the Kaggle website indicating the overall changes in the features based on the autism type or person's autism relevance. These features are utilized with the unbalancing of the data indicating the SMOTE feature of the design to establish the overall class labels with AUTISM and NO -AUTISM. We have implicated the overall dataset features and its functionalities in figure-1.

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 the overall dataset description

The figure -2 describes about the overall bock diagram feature modelling of the proposed IPD model. The proposed IDP algorithm and its loss formulations are effectively implemented in section 2.c and 2.d. With stated in figure-2 the initial process of the design is indicated with effective weight parametric as mentioned in the IDP algorithm and its formulations. Our work on the IDP indicates the specific probabilities matching of the features that are effectively estimated with multi objective functionalities in the dataset.

Hence theses feature relates the overall validation accuracy to be more precise and better for every iteration. The overall loss is esteemed with custom function with log loss on the expected probabilities for each feature effecting the Autism.

Algorithm for IPDM (Improved Probabilistic Dense Model)

Input: Let X be the overall cleaned data, X_{cm} *,* X_{mp}*,* X_{Fc}*,* X_a *be the layer inputs responses for the design flow*

Output: Y be the final outcome of the IDDM+CNN filter.

Procedure: CNN approach:

For i= 1:M do

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

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

$X_{fc} = \sum_{j=1}^{N} \quad X_{cm} * w_{n+1} + X_{mp} * H(k)$ *(1)*

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

End loop

Model1 = {X_{cm} ,X_{mp}, X_{Fc}, X_a} (2)

End Procedure

Loss Estimation

Since we know thatm ∝loss, hence the estimated speed for a given circuit is obtained with expected probability of loss that is governed with (1) and (2) as representing using Conditional expected probability:

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

Assuming the P(X) = probability of addressing the data for each iteration as mentioned above. The conditional feature with probability on the data addressing with expected time is represented as E(X∪T)=E(X)+E(T) if both the Time and data acquisition are Linearly addressed. As the data is varied and time would vary with every iteration a nonlinear approach is suited for the proposed design. Hence,

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

Similarly for Y we have,

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

Finally overall expected Probability with higher speed variant is:

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

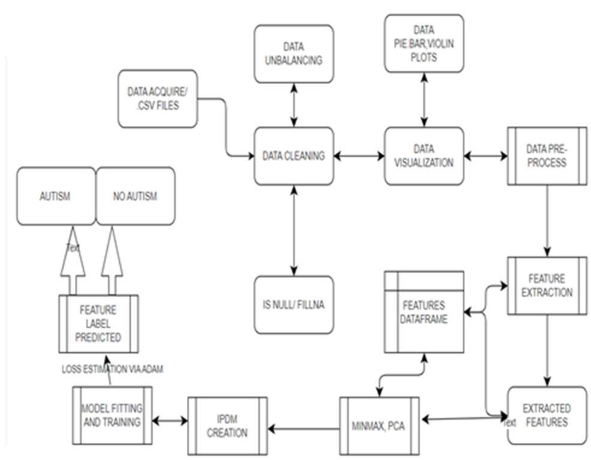

Figure 2: Representing the overall block diagram for autism classification using Deep learning model.

RESULTS AND DISCUSSION

The experimental model and its behaviour on the proposed model indicating the overall features of the design with missing, feature visualization and analysis with accuracy and loss graphs as mentioned below.

Experimental Setup

We implicate the dataset with local directories improvising the overall characteristic traits for autism indicating the different analysis report with algorithms as tabulated in table -1. The visual graphs with different aspects on the analysis part effectively sorted with different scores are tabulated in figure 3.

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 with no missing values.

Analysis on Accuracy

The overall accuracy observed with classification metric and its implemented results are tabulated in table-1 indicated the outperform with other algorithms.

	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

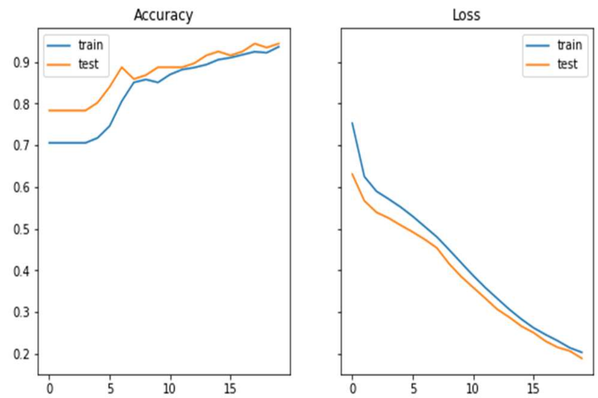

Figure 4: representing the overall Training and Training loss and Accuracy.

The above figure describes the overall accuracy for training and testing till 95% indicating the best accuracy from the existing machine learning algorithms. While the loss is effectively reduced when compared to other algorithms.

Tabulations

The below table 1 shows the Representation of Existing algorithms with proposed Algorithm (IDP) in various parameters like Accuracy, Sensitivity, Secificity, F1 – Score, Recall and Precision values.

TABLE 1

ALGORITHMS	ACCURACY	SENSIVITY	SECIFICITY	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***	***96***	***95***

CONCLUSION & SCOPE

Our proposed prediction models based on DL techniques can be utilized as an alternative or even a helpful tool for physicians to accurately identify ASD cases for people of different ages. Additionally, the feature importance values were calculated to identify the most prominent features for ASD prediction by employing 95% prediction results are observed indicated with our proposed work.

Scope:

Much effective features with more than 50 are to be implemented to realize the overall dataset pruning and testing effectiveness based on the Long Short Term Memory (LSTM) and other Service-Oriented Architecture (SOA) architectures.

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