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# ASD Classification in Adolescent and Adult Utilizing Deep Neural Network

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**ABSTRACT**
Autism Spectrum Disorder (ASD) is one of the neurological illnesses affecting the behaviour and communicative skills of an individual. It hampers the recognition capability of an individual. Hence it is the primary responsibility towards the affected individuals with ASD for early detection to minimize its effect. ASD clinical diagnosis procedure is lengthy and expensive. So, against the procedure, ASD datasets are stored in authenticated sites like Kaggle and UCI Machine Learning (ML) repository to carry out clinical research. The data from all the category of individuals including adult, adolescent, child and toddler got collected by a mobile based ASDTest app with certain screening questions. The proposed method covered the category of adolescent and adult datasets with implementation of Landmark Isomap for dimension reduction and then improved Deep Neural Network prediction with classification (i-DNNPC) architecture for detecting ASD class. The evaluation of performance parameters confirmed the accomplishment of i-DNNPC classifier model.

***Keywords:*** *ASD, Classification, i-DNNPC, Landmark Isomap, Performance parameters.*

## 1. INTRODUCTION

ASD is a neurodevelopment illness in individuals which is marked by repeated behaviors and loss of socio-communicative skills [1]. It's symptoms are marked in an individual from the first 6 months of life which increases leading to impairment in socio-communicative skills and repeated behaviors by 18 to 36 months of life [2]. The general strategy of diagnosing ASD is extensive and expensive. So as a cover up, this research focuses on detection of ASD class upon adolescent (12 to 16 years) and adult (17 years and above) individuals utilizing Deep Learning (DL). The research also utilizes the "Autism Spectrum Quotient (AQ-10)" for both category of individuals with 10 number of screening questions in each category [3]. UCI ML repository formed the source from where the datasets used in this work are collected which have 21 attributes with single output class. At present, various ML as well as DL techniques are utilized to classify ASD class in addition with attribute reduction techniques and validated by evaluating performance parameters. Hence the approach is quick, cost effective and clinically acceptable.

Section 2 describes the state of art works with distinct classification architectures, Section 3 outlines the datasets gathered for the investigation, section 4 describes the proposed approach, in section 5 the result is being discussed and finally, section 6 is concluded with a conclusion.

## 2. LITERATURE SURVEY

The researcher investigated upon 1452 instances with 21 features belonging to all category of individuals which were fetched via the ASDTest app introduced by the researcher himself based upon Q-CHAT and AQ-10 screening questionnaire [4]. The toddler dataset was found unbalanced and excluded from the investigation. The rest datasets containing 1100 cases were applied with wrapping filtering method for extracting features followed by implementing Naïve Bayes (NB) [5] and Logistic Regression (LR) [6] for classifying ASD class. The result got validated by performance parameters which established maximum performance by LR classifier model upon adult dataset.

Further the researchers investigated upon the same datasets gathered by ASDTest app thereby dropping the

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toddler instances due to their unbalanced nature and identified fewer influential features [7]. The datasets containing 1100 cases were employed with Variable Analysis (VA) for feature extraction followed by applying Repeated Incremental Pruning to produce Error Reduction (RIPPER) [8] and C4.5 Decision Tree (DT) [9] classifier models for ASD classification. The performance of adolescent dataset got confirmed by the assessment of performance parameters.

With an intension of proposing a Rule based ML (RML) [10], the researchers again investigated upon 1100 instances fetched via ASDTest app with all toddler instances being dropped off. The behavior of eight ML classifiers: C4.5, Bagging, CART, RIDOR, RIPPER, Boosting, PRISM, Nnge [11] was compared with that of RML which showed the maximum efficacy among all.

Based up on the supervised learning, authors investigated upon adult, adolescent as well as child datasets for detecting ASD [12]. The datasets were fetched from the UCI ML repository comprising of 21 attributes and an output class type with 1100 number of instances. The analysis involved pre-processing of the data and then classification by making use of SVM, KNN as well as Random Forest (RF) classifier models [13]. The pre-processed data got divided into 80 percent training data and 20 percent test data. The performance parameters authenticated the classifier model's performance.

Investigators gathered toddler dataset from Kaggle and rest other datasets from UCI repository having 1054 and 1100 cases respectively with 21 features in each dataset [14]. The analysis applied Principal Component Analysis (PCA) [15] to reduce the dimension followed by employing DNN architecture for ASD classification. Adult dataset got validated with maximum performance.

## 3. DATA COLLECTION

The ASD adolescent [16]and adult [17] datasets got collected from the UCI ML repository which are same with that of data collected by ASDTest app. There are 104 and 704 number of cases available in adolescent as well as adult datasets respectively with 21 attributes in each dataset. In addition, the datasets are also marked with the presence of missing data in some attributes such as "ethnicity" as well as "Who_completed_the_test". The nature of the attributes in datasets is continuous, categorical and binary type. In adolescent category, out of 104, 63 and 41 number of cases belong to ASD as well as no ASD class type. After discarding the missing values, the total number of cases dropped to 98 out of which 62 and 36 number of cases belong to ASD as well as no ASD class. In adult category, out of 704, 189 and 515 number of cases belong to ASD as well as no ASD class type. After discarding missing data, total number of instances dropped to 609 out of which 180 and 429 number of cases belong to ASD as well as no ASD class.

## 4. METHODOLOGY

The input adolescent and adult ASD datasets gathered from UCI repository are firstly pre-processed and then classified into ASD and no ASD class type. The research considered two cases: missing as well as complete data in both datasets. During pre-processing, the raw inputs are standardized to be fit in a specific range. In the next step of pre-processing, the standardized inputs are fed to Landmark Isomap model for dimension reduction in the datasets. Training data then trained the proposed i-DNNPC architecture with training parameter of 0.8 and test data tested the trained architecture with test parameter of 0.2 [12]. The performance measures like accuracy (Acc), specificity (Spe), sensitivity (Sen), Co-efficient of determination (R-Squared), Mean Square Error (MSE) as well as Root Mean Square Error (RMSE) evaluated the performance of trained i-DNNPC model for classification. The flow chart of the proposed work is represented in Fig. 1.

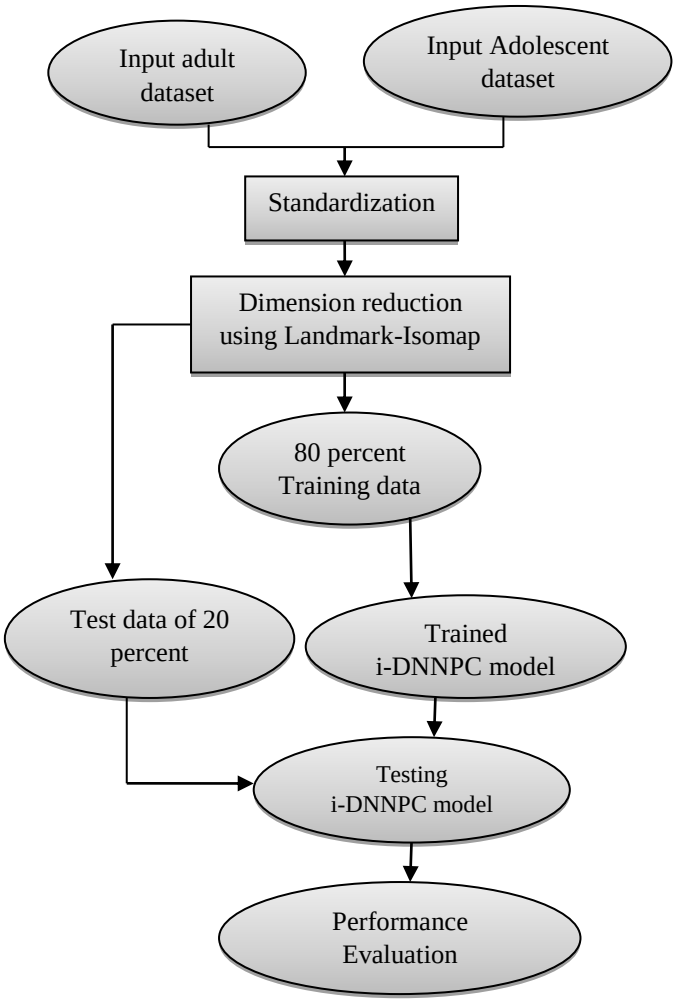


**Figure 1** Flow diagram of the proposed method

### *4.1. Pre-processing*

It is not advisable to directly feed raw data to classifier model for classification. Before that the collected datasets from the UCI ML repository are pre-processed. At the time of pre-processing, both missing as well as complete data in the prescribed datasets underwent standardization and then, dimension reduction by Landmark Isomap models.

#### *4.1.1. Standardization*

The raw adolescent and adult datasets are not properly scaled as the attributes of the datasets lack similar scaling. So firstly, the data in both the datasets are standardized using mean standard deviation method [18]. The standardized data is mathematically expressed by equation (1)

$$Sta\_X = \frac{(x - x_{mean})}{(x_{std})} \tag{1}$$

where, x represents a specific value of input X, $x_{mean}$ is the mean value of X and $x_{std}$ represents standard deviation of the X.

#### *4.1.2. Dimension reduction using Landmark Isomap*

As the input attributes in ASD datasets are non-linearly related, hence the proposed work utilized Landmark Isomap model for dimension reduction which is an advancement of Isomap in terms of speed [18-23]. It emphasizes in

1. Finding out a neighborhood graph G for the observed data $\{x_i\}$ in a particular way. Suppose, G contains $x_i x_j$ iff $x_j$ is one of the k-N neighbors of $x_i$. Alternatively, G may contain the edge $x_i x_j$ iff $|x_i - x_j| < \varepsilon$, for some $\varepsilon$.

2. Computing the shortest paths in the graph for all pair of data points. Every edge $x_i x_j$ present in graph is weighted by its respective Euclidean distance $|x_i - x_j|$, or by some other matric.

3. Applying multidimensional scaling (MDS) to the resulting shortest-path distance matrix D for finding a new embedding of data in the Euclidean space, approximating Y [24-26].

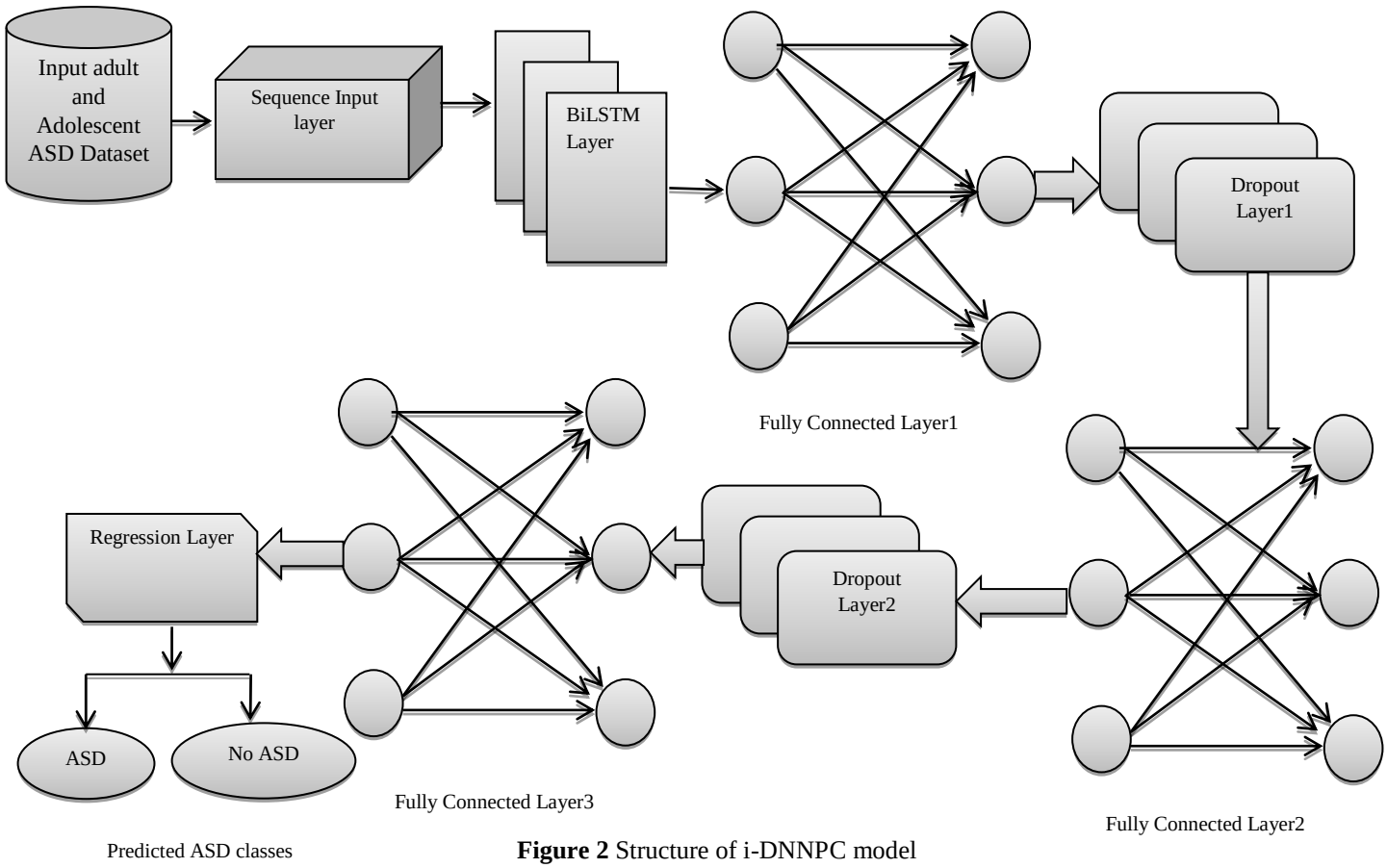


**Figure 2** Structure of i-DNNPC model

### *4.2. Improved Deep Neural Network prediction with Classification architecture*

The pre-processed adolescent as well as adult data are given to the i-DNNPC architecture for training and testing the model [27]. According to training parameter of 0.8, 80 percent of pre-processed data trained the proposed architecture and according to test parameter of 0.2, 20 percent of pre-processed data tested the architecture. A clear view of the i-DNNPC architecture is presented in Fig. 2. It comprises of one sequence input layer, a Bi Long Short Term Memory (BiLSTM) layer [20], 3 Fully Connected (FC) layers [21], 2 dropout layers [22] and a regression layer [23].

The BiLSTM layer having 100 hidden units takes an input sequence size of 3. It uses 'tanh' state activation function and 'sigmoid' gate activation function, learn rate factor of 1. It produces 200 outputs from 3 inputs. This layer uses 'sigmoid' activation function as given in equation (2):

$$\sigma(x) = (1 + e^{-x})^{-1} \tag{2}$$

Following BiLSTM layer, a FC layer is connected which takes an input size of 200 and produces 50 outputs. It uses a learn rate factor, 1, and null bias L2 factor [28-32].

Next to first FC layer, drop out layer is used which is based on the probability of dropping out the input entries [33]. The best value of probability is given by 0.5.

Following dropout layer, the second FC layer is connected for more efficient classification, which takes an input size of 50 and produces an output size of 20 with learn rate factor of 1, and null bias L2 factor [34-36].

The second dropout layer is connected next to fully connected layer with same probability of 0.5.

Following the second dropout layer, the third fully connected layer is connected which takes 20 inputs and produces one output with a bias of 0.2666, which is fed to regression layer to predict 1 output ASD class [37].

### *4.3. Performance Parameters*

Performance parameters validate the classifier model's performance. In this research work, the parameters: Acc, Spe, Sen, R-Squared, MSE as well as RMSE are estimated from True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values in confusion matrix [14].

## 5. RESULT

The proposed approach covers the adolescent as well as adult category of individuals. In case of adolescent dataset with missing data, the pre-processed data having 3 attributes trained the i-DNNPC architecture with a training parameter of 0.8, maximum epoch of 200, initial learn rate of 0.05, learn rate drop period (LRD) of 100 s, drop factor of 0.5, training duration of 27 s and finally, 100 number of hidden units. Fig. 3 represents the training of i-DNNPC architecture in case of adolescent missing dataset from where the RMSE is found to be nearly 0.1. The trained model is then tested by the test data with a test parameter of 0.2. Out of 98 number of instances, the training instances of 78 and test instances of 20 got formulated according to the training parameter of 0.8 and test parameter of 0.2 respectively. Out of 20, 8 as well as 11 number of cases are correctly classified under ASD and no ASD class respectively. Furthermore, one case is found as false classification under no ASD class. The performance of the proposed classification architecture got authenticated by assessment of performance parameters.

In case of adolescent dataset with complete data, the same procedure is repeated as in case of missing data with almost same training specifications. The training duration is found to be 26 s. In both cases, the training duration does not make a huge difference as the number of adolescent training instances in both missing as well as complete datasets is much closer. Fig. 4 represents the training of i-DNNPC architecture in case of adolescent complete dataset from where the RMSE is found to be nearly 0.1. Out of 104 cases, the training cases of 83 and test cases of 21 drew out according to the training parameter of 0.8 and test parameter of 0.2 respectively. Out of 21, 9 as well as 10 number of cases are correctly classified under ASD and no ASD class respectively. Furthermore, 2 cases are found as false classification under ASD class. The performance parameters are assessed to check the performance of the proposed classification architecture.

For adult dataset with both missing as well as complete data, the pre-processed data with 3 attributes trained the i-DNNPC architecture with same training specifications except the training duration. In case of missing data, the training took 110 s for its completion whereas the duration of training in case of complete data is 115 s due to a greater number of training instances. Fig. 5 and Fig. 6 represents the training of i-DNNPC architecture in case of adult missing as well as complete dataset from where the respective RMSEs are found to be nearly 0.15 and 0.2 respectively. For missing data, out of 609 cases, the training cases of 487 formulated according to training parameter of 0.8 trained the i-DNNPC architecture and rest 122 test cases formulated according to test parameter of 0.2 tested the classifier model. 36 and 81 number of cases are found correctly classified under ASD and no ASD class. There are also 2 and 3 number of cases found to be wrongly classified as ASD and no ASD class. For complete data, among 704 instances, the training and test instances are 563 as

well as 141 respectively according to training and test parameters. It is found that 37 and 94 number of instances are correctly classified under ASD and no ASD class. Some wrong classifications are also found such as 3 and 7 number of instances misclassified as ASD and no ASD class. The performance parameters are assessed to check the performance of the proposed classification architecture. Table 1 represents the performance of trained i-DNNPC model upon both adolescent as well as adult datasets with other state of art methods. Fig. 7 and Fig. 8 show statistical analysis of the proposed method with other state of art methods for adolescent and adult respectively.

In all the figures showing the training process of i-DNNPC model, number of epoch is present in X-label and training RMSE is present in Y-label. In the figure of statistical performance analysis of i-DNNPC classification model, the performance parameters and the value of performance parameters are present in X-label as well as Y-label respectively.

The performance of the trained model upon missing datasets in both adolescent and adult cases is found out to be stronger in comparison to complete ones. Furthermore, due to the presence of more number of instances, adult dataset performed better in comparison to adolescent one.

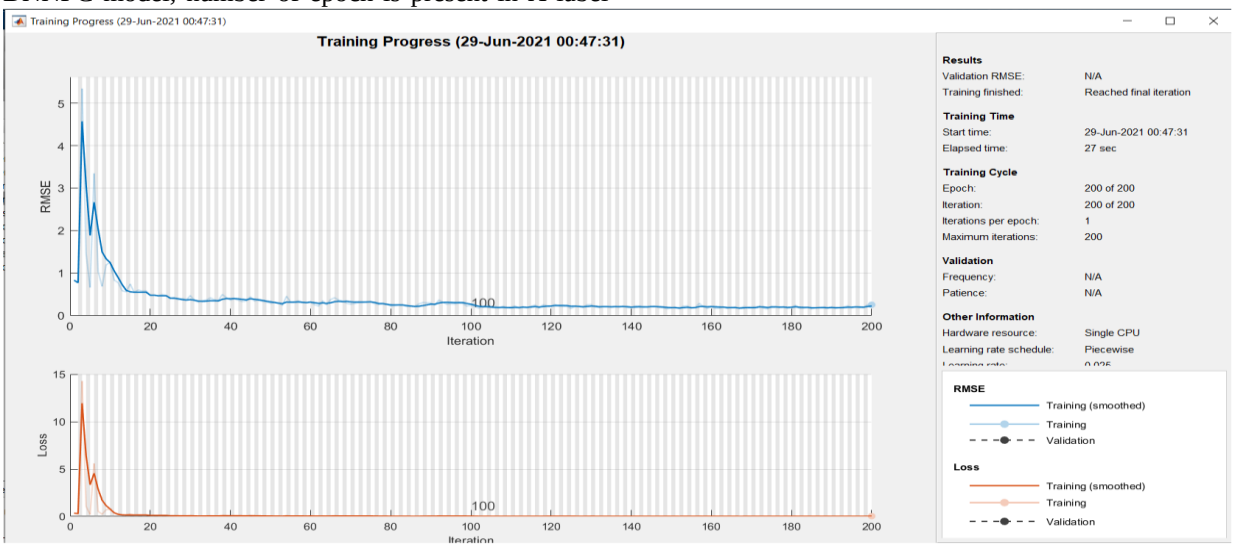


**Figure 3** Training of i-DNNPC architecture in case of adolescent missing dataset

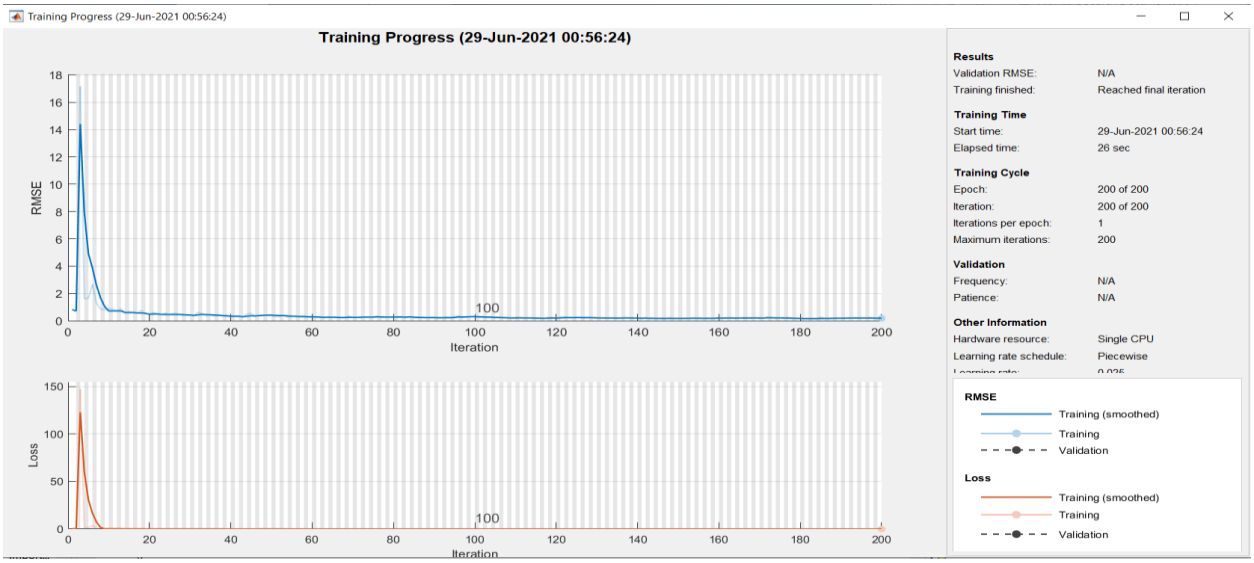


**Figure 4** Training of i-DNNPC architecture in case of adolescent complete dataset

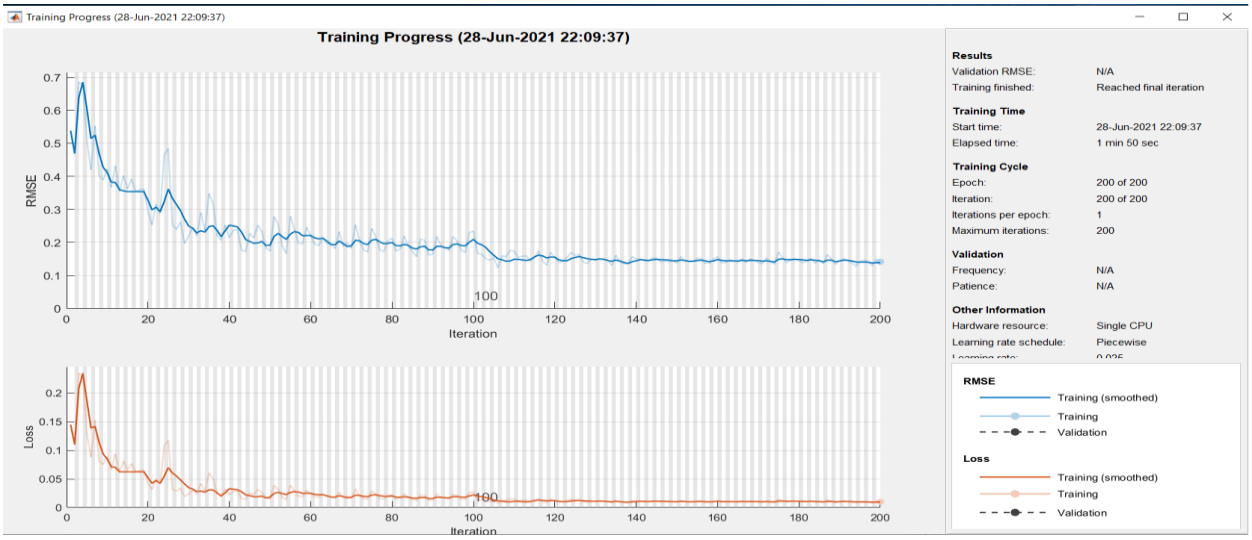


**Figure 5** Training of i-DNNPC architecture in case of adult missing dataset

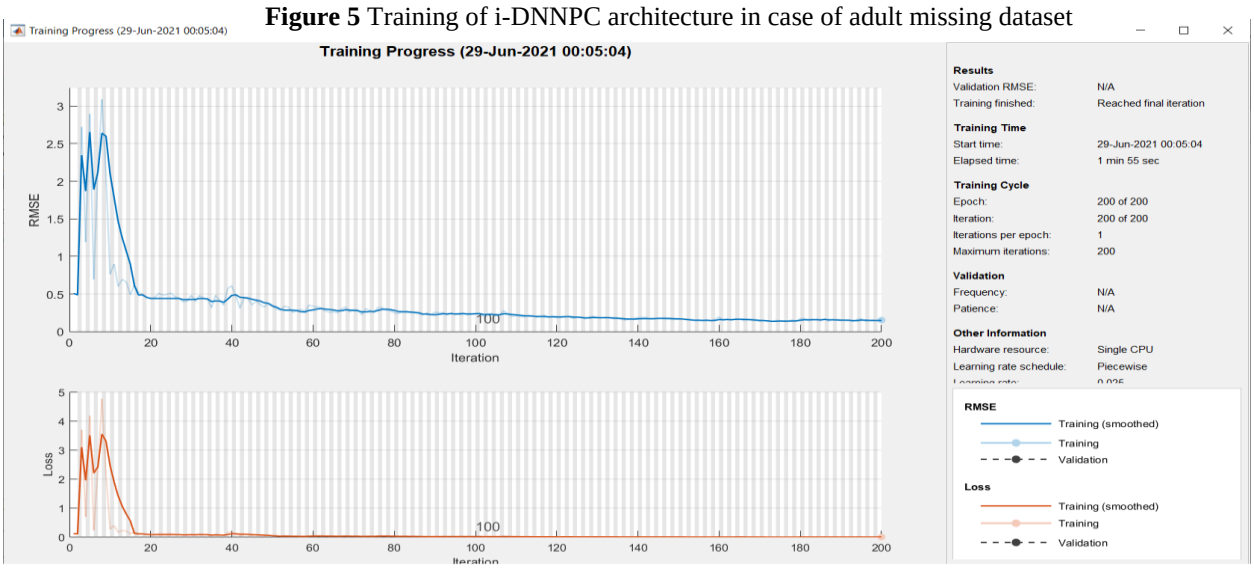


**Figure 6** Training of i-DNNPC architecture in case of adult complete dataset

**Table 1.** Performance of the proposed method along with other state of art methods

| Paper and classifier model | | Acc | Sen | Spe | RMSE | MSE | R-Squared |
|---|---|---|---|---|---|---|---|
| [7]2018 (C4.5) | Adolescent | 0.855 | 0.905 | 0.780 | - | - | - |
| | Adult | 0.885 | 0.810 | 0.930 | - | - | - |
| [4] 2019 (NB) | Adolescent | 0.913 | 0.913 | 0.853 | - | - | - |
| | Adult | 0.957 | 0.957 | 0.966 | - | - | - |
| [10] 2020 (RML) | Adolescent | 0.875 | 0.875 | 0.810 | - | - | - |
| | Adult | 0.940 | 0.945 | 0.970 | - | - | - |
| [12] 2020 (KNN) | Adolescent | 0.880 | 0.880 | - | - | - | - |
| | Adult | 0.949 | 0.947 | - | - | - | - |
| [14] 2021 (DNN) | Adolescent | 0.842 | 1 | 0.727 | 0.990 | - | - |
| | Adult | 0.892 | 1 | 0.843 | 0.426 | - | - |
| Proposed method adolescent (MD) | | 0.950 | 0.888 | 1 | 0.223 | 0.050 | 0.789 |
| Proposed method adolescent (CD) | | 0.904 | 1 | 0.833 | 0.308 | 0.095 | 0.611 |
| Proposed method adult (MD) | | 0.959 | 0.923 | 0.975 | 0.202 | 0.041 | 0.811 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Proposed method adult (CD) | 0.929 | 0.840 | 0.969 | 0.266 | 0.070 | 0.669 |

MD refers to Missing Data

CD refers to Complete Data

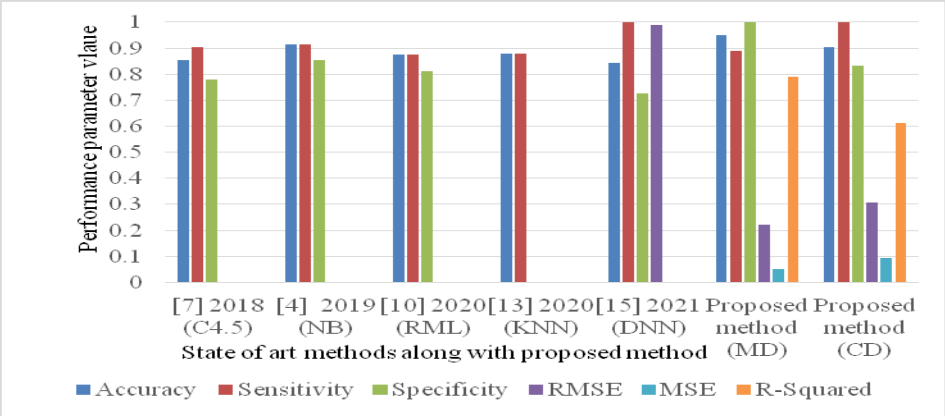


**Figure 7** Statistical analysis of proposed method along with other state of art methods for adolescent

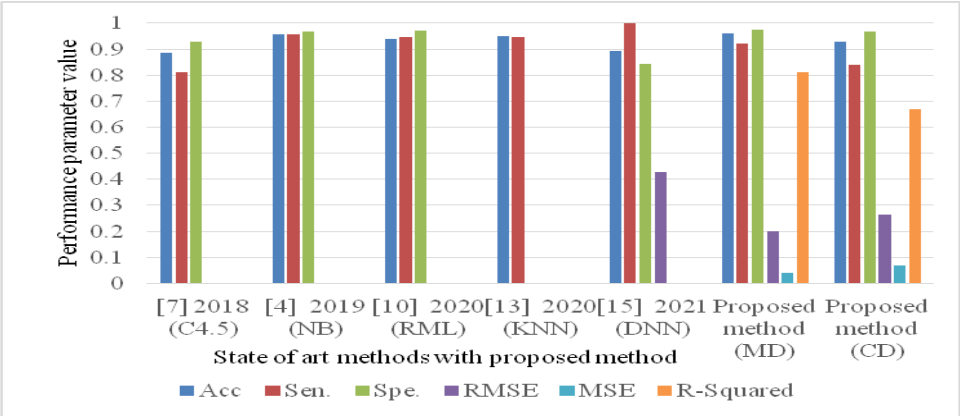


**Figure 8** Statistical analysis of proposed method along with other state of art methods for adult

## 6. CONCLUSION

The proposed approach engrosssed on detecting ASD in adolescents and adults for improving their quality of life. The research utilized Landmark Isomap for dimension reduction, then 80 percent of the processed data trained the proposed i-DNNPC architecture and 20 percent data tested the trained architecture. The evaluated performance parameters ascertained the efficiency of trained classification architecture for classifying ASD classes. In case of complete data, due to the presence of a bit more misclassification cases under ASD class, the trained architecture in case of missing data showed supremacy in comparison to the complete one. Furthermore, the adult dataset performed better than adolescent one because of a greater number of instances in adult dataset. The overall performance of both the datasets is acceptable clinically. Altogether the certainty of employing DNN models to detect ASD can be carried out efficiently. The research being limited to two datasets can be further extended to toddler as well as child datasets.

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