International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I7P214
Volume 71 Issue 7, 132-146, July 2023

Original Article

Attn_CNN_LSTM: IoT-Based Automated Alzheimer's Disease Classification using Deep Learning Approach

Anjani Yalamanchili[1], D. Venkatasekhar[2], G. Vijay Kumar[3]

[1,2]*Department of Information Technology, Annamalai University, Annamalai Nagar, Tamil Nadu, India.*
[3]*Department of Computer Science and Engineering, SSCET, Challapalli, Andhra Pradesh, India.*

[1]*Corresponding Author : anjaniyalamanchili@gmail.com*

Received: 30 January 2023 Revised: 18 June 2023 Accepted: 21 June 2023 Published: 21 July 2023

Abstract *- Accurate recognition of Alzheimer's disease (AD) is a major concern in the Internet of Things (IoT) data. As IoT data deliver valuable recognition in the case of AD, suitable techniques are preferred for the detection process. Manual examinations undertaken by clinicians are found to be time-consuming and highly complex over instantaneous situations. Diverse approaches are developed for earlier stage AD detection but are found to be less robust, difficult in handling data, less convergent, time-consuming and lead to over-exploited losses. Hence to conquer the existing complexities, the proposed research article introduces an efficient automated deep learning (DL) based AD recognition using IoT data. The processes included in AD classification are data acquisition, Pre-processing, feature extraction, feature selection and classification. The initial step of the proposed work is data acquisition which targets gathering IoT data from the Daphnet dataset. The gathered data are pre-processed using data normalization and balancing. Normalization is performed using the Z-score-based Median and Median Absolute deviation (ZS-MMAD) approach, whereas data balancing is done using the Synthetic Minority Over-sampling Technique (SMOTE) approach. The pre-processed data are fed into mean, variance, and covariance-based Principal component analysis (MVC-based PCA) to extract the relevant features. Optimal features are selected using the Tweaked Archimedes optimization algorithm (TAOA). The non-part of the experiment, Experiment (No freeze) and Freeze classes of AD, are effectively classified through an attention-based Cascaded convolutional recurrent framework (Attn_CNN_LSTM). The proposed research work is implemented using the PYTHON simulation tool, and overall accuracy of 95.68% is obtained in classifying AD.*

Keywords *- Deep learning, Alzheimer, IoT data, Optimization, Data balancing, Optimal features, Attention, Classification.*

1. Introduction

Alzheimer's disease (AD) is considered one of the most predominant diseases of dementia that is normally categorized as a syndrome occurring in a progressive or chronic nature [1]. AD is one of the leading death concerned diseases across the world. In accordance with the statistics of the world health organization (WHO), nearly 50 million people are influenced by this disease [2-3]. It is a neurodegenerative disease that generates mental disorders in humans, leading to the degradation of cognitive function and affecting thinking capabilities. Both elderly and young people are affected by this disease, but it usually occurs in older people, with gradual loss of understanding and memory as the most common symptoms [4-5]. By 2050, it is estimated that one in every 85 persons is expected to suffer from this deadly disease.

The total number of people affected by dementia is expected to spread to 82 million by 2030 and 152 million by 2050 [6]. It is predicted to commonly spread among people who live in less and middle-income countries [7-8]. Dementia has a psychological, economic, physical and social impact not only on the people affected by the disease but also creates difficulties for their families, carers and society. The caretakers of AD-affected patients are subjected to stress, frustrations, and emotionally challenged [9]. The cognitive function may be gradually minimized over time among the patients while the behaviour variations fluctuate throughout the day, which will be highly difficult for the caretakers to render positive correlation and effective handling [10-11]. It has been insisted that no significant treatments or medications are available to prevent AD progression.

Recently, healthcare data is progressively gaining more and more attention towards AD detection efficiently. Monitoring patients remotely can help physicians control temperature, heart rate, blood pressure, respiratory rate, etc. Automated data collection helps to minimize the complexities through processing diverse aspects [12-14]. Many forms of machine learning (ML) based AD detection approaches have been incorporated to exploit brain functions and structures [15].

The Internet of Things (IoT) data is widely adopted to gather patient information to analyze the presence of AD and render suitable treatment [16-17]. IoT technology has been established through the adoption of various sensors. In contrast, the condition of patients can be monitored through remote networks like global systems for mobile communication, wireless networks and so on.

The indoor movements and patient activities can be monitored from anywhere outside the home through the sensor installation over the patient's body or clothing [29]. By analyzing the collected data with the help of these sensors, they are sent to the appropriate health center to obtain significant information that physicians can use when deciding on appropriate treatment solutions [19-20].

Even though statistically based ML approaches like Support Vector Machine (SVM) have shown some advantages, DL-based approaches like Convolutional Neural Networks (CNN) have proven superior for early diagnosis. The security in transferring medical data needs better to mitigate risks by ensuring data integrity and confidentiality. Security protocols must be incorporated for maintaining the IoT-based healthcare data in the effective diagnosis of AD at early stages and offering appropriate treatment.

Various studies have been directed by several researchers worldwide; however, the actual cause of the disease remains unidentified. Whereas, despite the non-pharmacological and pharmacological treatments that researchers and physicians have recommended to support these patients affected by Alzheimer's, practically none of the treatments prevent the disease from developing.

Meanwhile, caring for these persons is required 24 hours per day; it is economically expensive and takes a lot of patience for the family. The development of IoT can continuously monitor the behaviour of patients affected by Alzheimer's abroad and at home and notify the critical conditions and the geographical location of healthcare personnel and family members. Therefore, a novel solution for monitoring patients' health conditions and tracking activities with the support of IoT devices has been focused on.

1.1. Contribution

The major goal of this research work is to recognize AD classes accurately. A novel DL-based method called Attn_CNN_LSTM is presented for early AD detection. Some prospective contributions for promoting the overall performance are described as follows.

- Initially, the IoT data were acquired from the Daphnet dataset, which was collected from integrating the neurodynamics and gait laboratory at the Wearable Computing Laboratory. Three classes, including non-part of the experiment, no freeze and freeze classes, are contained in the dataset.
- Secondly, the IoT data are pre-processed through the ZS-MMAD technique for normalizing the data within a particular range, and the normalized data are balanced using SMOTE approach. These steps are considered to solve the challenges of less data consideration and complex data processing.
- Thirdly, extract the relevant data features using MVC-based PCA to minimize the computational time and promote classification accuracy. From the extracted features, optimal features are selected using TAOA to minimize the data dimensionality issues and enhance the training ability.
- Finally, to introduce an efficient Attn_CNN_LSTM classification model based on the DL framework for the early detection of AD using IoT data. This model overcomes the challenges of degraded performance, increased rates of error and less classification accuracy.
- To assess the AD classification performance outcomes using various metrics like accuracy, precision, etc. and to compare the proposed model with different baseline methodologies to prove the superiority.

The rest of the paper is structured into substantial sections described as follows. Section 2 signifies the currently existing research works performed by various authors in the AD classification. Section 3 describes the workflow of the proposed methodology undertaken through data pre-processing, feature extraction, selection and classification. The results and performance analysis of AD classification based on the DL model are presented in Section 4. Section 5 describes the conclusion of the proposed work, followed by the future scope with references.

2. Related works

The necessity of accurate AD detection is increasing in the healthcare system, and most researchers have suggested diverse methodologies. Some of the research contributing to AD detection is summarized as follows.

Machado *et al.* [21] proposed an ontology-based computational approach that gathers physiological data from external applications of the IoT. The main objective of this research work was to determine the potentially critical behaviours of AD patients through the analysis of context predictions and context histories.

A simulator was also proposed to create activities regarding patients' everyday life. DCARE dataset simulator tool was used to generate the data, and they were created in accordance with ontology standardization. 1026 scenarios were created by the simulator to guide the AD prediction, whereas an average accuracy of 97.44% was attained. The real-time data obtained from IoT devices was not enriched, and rendering a suitable solution for the end user tends to be complex.

Oskouei *et al.* [22] developed IoT based healthcare support system for treating AD patients. The data was gathered by assembling multiple sensors installed at patients' homes and smartwatches to monitor the blood pressure level, temperature, etc. By observing AD patients at home, the movements and behaviour are noticed and based on that, and appropriate treatments are provided. Different communication protocols utilized smartwatches, including Web Sockets with authentication, auto-closed connection, Message Queue Telemetry Transport (MQTT) and hypertext transfer protocol (HTTP) in sensors. For tracing, a secure backend admin panel was used. An accuracy of 95% was obtained, but the emergency alerts were not properly maintained.

Zhou *et al.* [23] presented an approach to AD diagnosis based on an IoT monitoring system and DL classification approach. The main objective of this research was to minimize the acceleration cost regarding AD diagnosis. The screening tests of AD based on business and human-computer interaction were introduced to the internet system. The chief focus of this research was to estimate the recent memory loss across events and human-computer interaction. An essential solution can be obtained in case of zero-day or new attacks by monitoring the IoT devices. The normal and abnormal stages of AD can be classified, and this research enables rapid, enhancing testing and treatment process can be rendered. However, the major demerit was security requirements of IoT devices complicated.

Ahmed *et al.* [24] proposed an automatic IoT system for detecting and classifying brain MRIs based on DL and Arduino global mobile communication system (GSM). The regression principle is applied to MRI data by adopting a genetic algorithm. The noise present in the data was minimized through a bilateral filtering approach. The genetic algorithm is effectively used to generate the best fusion data from the source and reference data. CNN technique is applied for brain tumour classification, and the appropriate messages are sent to the patients through GSM. The proposed model was tested to classify abnormal and normal data, whereas an accuracy of 98.8% was obtained. The dataset consideration was less, and only minimal aspects were analyzed.

Chokri *et al.* [25] developed a prototype that offers psychological support services and ensures information transfer with high security, which a family member can analyze to prevent the AD-affected person. Through the adoption of wearable prototype data, they can be classified through CNN. Additionally, tracking a person's location can be enabled, and the data can be conserved through a steganography approach that permits decoding original data through the key. The presented prototype was highly useful for people who were affected by mild and moderate dementia. A higher accuracy rate of 99.38%, a precision of 99.23% and a specificity of 93.18% was obtained in facial recognition of AD patients. Due to the larger accumulation of data, the system speed was minimized. Table 1 compares existing approaches with their corresponding outcome and limitations.

Table 1. Review of existing AD classification methods

Author & Ref	Technique	Contribution	Performance	Limitations
Machado *et al.* [21]	Ontology-based computational approach	To determine the potentially critical behaviours of AD patients through the analysis of context prediction and context histories	Accuracy- 97.44%	More complexity.
Oskouei *et al.* [22]	IoT-based healthcare support system	To provide a healthcare support system based on IoT for treating AD patients	Accuracy-95%	Not suitably maintained emergency alerts.
Zhou *et al.* [23]	IoT monitoring system and DL classification approach	To reduce the acceleration cost concerning AD diagnosis. To evaluate the recent memory loss across events and human-computer interaction	Classified normal and abnormal stages of AD with better accuracy.	Complicating security requirements of IoT devices.
Ahmed *et al.* [24]	DL-GSM	To provide an automatic IoT system for detecting and classifying brain MRI	Accuracy-98.8%	Less dataset consideration and only minimal aspects were analyzed.
Chokri *et al.* [25]	CNN	To provide psychological support services and ensure information transfer with high security, which a family member can analyze to prevent the AD-affected person.	Accuracy-99.38%	Minimized system speed.

When surveying diverse existing AD detection and classification techniques, there are adversarial limitations like less system speed, difficulty considering huge data, less convergence rate, higher computational complexities and requirement of more computational resources. Also, they are subjected to higher chances of false rates, complicated security requirements, improper emergency alerts, overfitting issues, and the requirement of high training time to handle a larger accumulation of data. Due to the occurrence of enlarged complexities in the surveyed research articles, accurate AD detection cannot be obtained. Hence, an effective deep learning architecture is employed in the proposed research to overcome these limitations and obtain better classification accuracy.

3. Proposed Methodology

The principal attention of the proposed model is to develop an automated structure for the early detection of AD through IoT data classification. Still present scenario, there are no appropriate medications as AD is an irreversible and chronic brain disorder. The available medicines evolve with delays in treating AD, and early diagnosis can prevent the severity. Hence, early AD detection using IoT data retains a substantial role in preserving and observing its development. The proposed model's AD classification based on the DL model is presented to develop the overall classification accuracy. AD classification employs a generous role in the present era, generally when a massive amount of data is fed as the input. Accurate classification using abundant data, reduction of error and maximizing the training capability is highly challenging. This research article proposes an efficient automated DL-based AD classification approach to achieve better classification outcomes. The steps involved in the proposed AD classification model are listed as follows.

- Acquisition of IoT data
- Data Pre-processing
- Feature Extraction
- Feature Selection
- Multi-class classification

Figure 1 demonstrates the general architecture of the proposed AD classification model. The IoT data for performing AD classification are initially collected from the Daphnet dataset. Data pre-processing is performed to improve IoT quality and destroy distorted data. The IoT data are normalized and then balanced using the SMOTE algorithm. The pre-processed data are directed over the feature extraction process to extract the relevant data. The optimal features are then selected from the IoT data features to improve the classification accuracy. Finally, the multi-class classification of AD is performed to classify the accurate stages of AD. The elaboration of every process undertaken in the proposed model is explained in detail as follows.

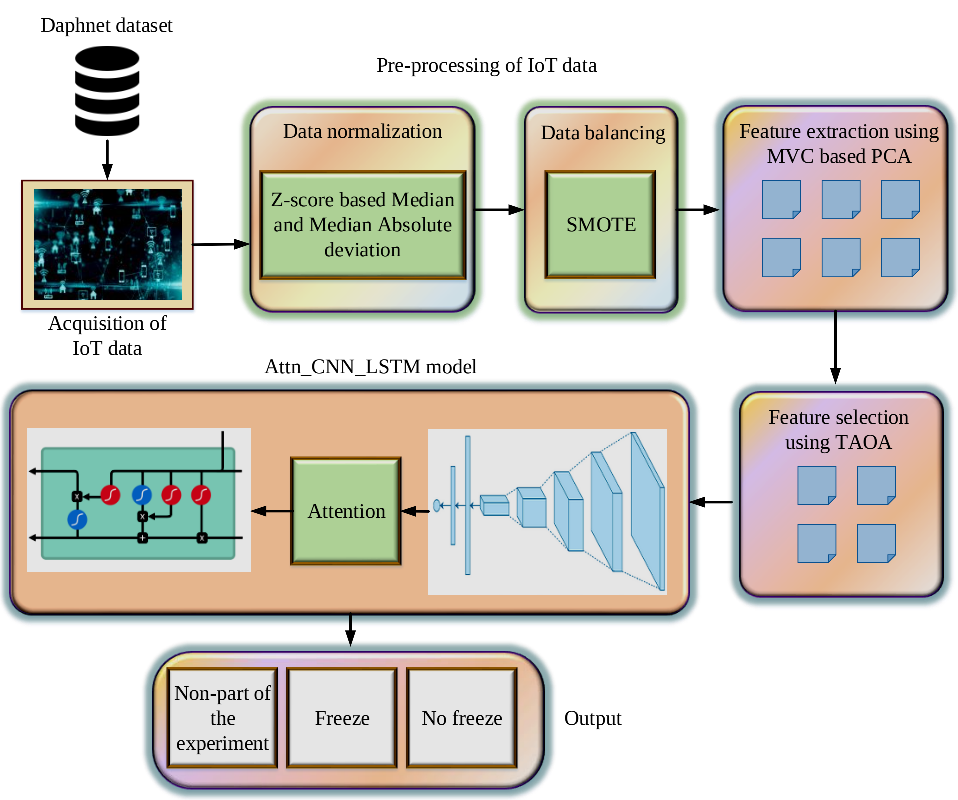


Fig. 1 General architecture of the proposed AD classification model

3.1. Data Pre-Processing

The collected IoT data from Daphnet dataset may be subject to numerous forms of influence that undesirably affects the overall classification performance. Hence, the data need to be pre-processed to eradicate any kind of distortion. The fundamental focus of data pre-processing is to eradicate unwanted distortions from the data so significant information can be utilized for the classification process. Huge amounts of original IoT data are collected from Alzheimer patients in the form of a Daphnet dataset and cannot be processed directly as manual processing tends to be difficult and consumes a huge amount of time; an automated pre-processing approach is used in the proposed research work.

3.1.1. Data Normalization

In most of the approaches, the min-max normalization approach is the most generally used normalization technique, but there generates a major disadvantage as the incapability of handling data outliers. To overcome the drawback, a new method called ZS-MMAD is used in the proposed research work that is found to be very simple and easy to employ over any dataset size. The proposed ZS-MMAD technique is robust over outlier concerns, applicable over any form of data and easy to implement. The proposed normalization technique based on the Z score can be expressed as follows.

$$ZS = \frac{\hat{\beta}_M - b_i}{\hat{\theta}_M} \quad (1)$$

From the above-mentioned expression, the Z score is signified as ZS, $\hat{\beta}_M$ represents the median (M) estimator, and median absolute deviation (MAD) is signified as $\hat{\theta}_M$. The M indicates the assessment of central tendency that is not delicate to outliers. The MAD determines the median of absolute deviations from M. The normalization technique employed can be suitable for any data length. ZS-MMAD helps to normalize the data to confirm that it converges over a standard normal distribution with M of 0 and MAD of 1. The data performance can be greatly improved through the outlier eradication from the collected data.

3.1.2. Data Balancing

When the distribution of classes in the data is uneven, the data tends to be imbalanced. Especially in IoT data, there emerges a lot of imbalanced data, and it wants to be balanced to attain improved classification accuracy and to ease data processing. In the proposed research work, a data balancing algorithm called SMOTE [26] is adopted for balancing the IoT data. SMOTE process is applied over the normalized data that can overcome the imbalanced data issues, increasing the minority class instances. SMOTE is an algorithm that undergoes data balancing by generating artificial data points based on the normalized IoT data. The SMOTE process tends to be an advanced oversampling version, whereas the artificial points that vary slightly from the original IoT data are created.

Table 2. SMOTE algorithm

Algorithm: Data balancing using SMOTE
Begin
Input: Normalized IoT data
Output: Balanced IoT data
Begin
Consider **W** as the original dataset
Describe the set of minority class instances as **Y**
for each instance **b** in **Y**
Identify the k-nearest neighbor (instances of minority class) to **b** in **Y**
Obtain **f** by randomizing one from **k** instances
Difference = $\mathbf{b} - \mathbf{f}$
Gap = Random number between 0 and 1
$\mathbf{o} = \mathbf{b} + \mathbf{difference} * \mathbf{gap}$
Add **o** to **W**
End for
End

The SMOTE process greatly circumvents the overfitting issues. Table 2 describes the procedure of SMOTE algorithm.

SMOTE algorithm works in the way of slight data point movement in the direction of its neighbour. The artificial data points are not an exact copy of the original data point, and also, it is not too dissimilar from the original interpretations in minority class instances. Through the application of SMOTE algorithm, the data can be made balanced, which helps to enhance the classification performance.

3.2. Feature Extraction

The huge quantity of data collected through IoT terminals leads to higher dimensions and unfavorable aspects like errors and higher time consumption. Hence, it is required to minimize the data size and compress the IoT data to enhance the system's efficiency. MVC-based PCA is a dimensionality reduction approach commonly used in data mining approaches. The MVC-based PCA can utilize a few linearly independent major components to expose the original variables. The assumption of collected samples can be expressed as,

$$P = (p_1, p_2, p_3, \ldots\ldots p_n) \quad (2)$$

From the above expression P represents the collected IoT data samples after pre-processing. For the uniform representation of diverse feature dimensions in the sample data, it is required to center the piece initially. The uniform feature dimension $\hat{P}$ is shown as

$$\hat{P} = (p_1 - \eta_1, p_2 - \eta_2, p_3 - \eta_3, \ldots\ldots p_n - \eta_n) \quad (3)$$

Where $\eta_1 to \eta_n$ represents the mean values

$$\eta_u = \frac{1}{k}\sum_{v=1}^{k} p_u^v [1,1,1, \ldots.\, 1^U]\,; u = 1,2, \ldots n \quad (4)$$

The mean vector of IoT data is represented as η_u, the total number of samples are denoted as k, the data with specified sample range is indicated as p_u^v and over any size, the sample variance can be represented as,

$$Var(p_u) = \frac{1}{k}\sum_{u=1}^{k}(p_v^{\sim u})^2 \quad (5)$$

Where the Uniform sample range is $p_v^{\sim u}$ and the covariance of dimension can be represented as,

$$COV(p_v, p_x) = \frac{1}{k}\sum_{u=1}^{k} p_v^{\sim u}\, p_x^{\sim u} \quad (6)$$

Where the row data sample and column data sample are mentioned as $p_v and p_x$, and the uniform row and column data sample are given as $p_v^{\sim u} and p_x^{\sim u}$. The assumption of the matrix $D = 1/kP^{\sim U}P^{\sim}$ can be made as

$$D = \begin{vmatrix} \frac{1}{k}\sum_{u=1}^{k} p_1^{\sim u}p_1^{\sim u} \ldots\ldots \frac{1}{k}\sum_{u=1}^{k} p_1^{\sim u}p_n^{\sim u} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \frac{1}{k}\sum_{u=1}^{k} p_n^{\sim u}p_1^{\sim u} \ldots\ldots \frac{1}{k}\sum_{u=1}^{k} p_n^{\sim u}p_n^{\sim u} \end{vmatrix} \quad (7)$$

The C diagonal matrix represents the sample variances, and the off-diagonal elements denote the covariances. For dimensionality minimization, the features are selected based on the ortho-normal unit. The pairwise data covariance possesses under linear representation; orthonormal unit basis signifies the variance with a higher value. The matrix acts symmetric, whereas the transition matric after basis transformation tends to be diagonal. The Eigenvectors respective to diverse Eigenvalues are orthogonal over each other as the matrix is symmetric.

$$R^U DR = R^U \frac{1}{k} P^{\sim U} P^{\sim} R = \frac{1}{k}(S^U S) = \varDelta = \begin{bmatrix} \delta_1 \ldots 0 \\ \vdots \ddots \vdots \\ 0 \cdots \delta_n \end{bmatrix} \quad (8)$$

The orthonormal basis sought is represented as R and S denotes the data attained after dimensionality reduction. Through the employment of MVC-based PCA, a huge group of interrelated variables reduces into fewer dimensions to gather a substantial variability portion of original variables. After employing MVC based PCA approach, the data dimensions can be extensively minimized, redundant data can be eradicated, and relevant features can be extracted.

3.3. Feature Selection

Some features are extracted from the IoT data through the feature extraction process. When all the features are processed through the classifier, it consumes high processing time and more chances of error. Hence, the most discriminant features are selected for classifying AD-based IoT data. The proposed research work selects appropriate features by adopting the TAOA approach. The AOA [27] technique employs based on the individual population having accelerations, random volumes and density. In AOA, the individuals utilize locations dependent upon density, acceleration and volume. To advance the AOA performance, the TAOA method is presented through the integration of a new parameter called Z_k that is included over upper and lower limits to enhance the exploration and exploitation balance of search space. Initially, the fitness function is evaluated as the features that possess maximized classification accuracy and minimized error. At every iteration, the individual's volume and density get updated. The location of every individual can be overcome through volume, density and acceleration. The diverse steps involved in the TAOA approach are given as follows.

Step 1: Initialization process

The initialization process of every individual can be mathematically formulated as,

$$p_u = LOB_u + RAND \times (UPB_u \times LOB_u), u = 1,2\ldots..N \quad (9)$$

From the above equation p_u specifies the u^{th} individual, the lower and upper bound can be represented as LOB_u and UPB_u correspondingly. The number of individuals is denoted as N and $RAND$ indicates the vector of range $[0,1]$. The reset density RD_u and volume Vol_u of every u^{th} individual can be mathematically expressed as,

$$RD_u = RAND \quad (10)$$

$$Vol_u = RAND \quad (11)$$

The start acceleration of u^{th} object can be mathematically defined as,

$$ACC_u = LOB_u + RAND \times (UPB_u \times LOB_u) \quad (12)$$

In this section, select the individual with the best fitness value by allocating p_{best}, RD_{best}, Vol_{best} and ACC_{best}. The finest individual is denoted as p_{best} whereas RD_{best}, Vol_{best} and ACC_{best} represents the density, volume and acceleration.

Step 2: Renewal of Volume and Density

The volume and density of u individual over $t+1$ repetition can be mathematically reorganized as,

$$RD_u^{t+1} = RD_u^t + RAND(RD_{best} - RD_u^t) \quad (13)$$

$$Vol_u^{t+1} = Vol_u^t + RAND(Vol_{best} - Vol_u^t) \quad (14)$$

From the above equations RD_{best} and Vol_{best} denotes the density and volume of the finest individual possessing a uniformly distributed random number $RAND$.

Step 3: Transfer Operator and Density Factor

Initially, the individual collision occurs to attain symmetric conditions. The condition is provided by assisting the transfer operator (TO), changing the assessment from exploration to the exploitation stage and is defined as,

$$TO = Exp\left(\frac{t - t_{max}}{t_{max}}\right) \tag{15}$$

The TO increases gradually with respect to time till obtaining one and from the above expression, t indicates the iteration number and t_{max} represents the maximum iteration. The density declining factor (DDF) accompanies global to local search.

$$DDf^{t+1} = Exp\left(\frac{t_{max}}{t_{max}} - \left(\frac{t}{t_{max}}()\right)\right) \tag{16}$$

The DDf^{t+1} declines when time traverses, which renders the ability to converge in the preceding region.

Step 4: Exploration Phase

The collision occurs between the individuals when $TO \leq 0.5$, whereas the elements are selected randomly which is random and study the object acceleration as,

$$ACC_u^{t+1} = \frac{RD_m + Vol_m + ACC_m}{RD_u^{t+1} + Vol_u^{t+1}} \tag{17}$$

From the above expressions RD_m, Vol_m and ACC_m indicates the density, volume and acceleration of the random material. If $TO \leq 0.5$, the exploration can be guaranteed by 1/3 of iterations. If the value of TO is not 0.5, diverse variations arise in exploration-exploitation performance.

Step 5: Exploitation Phase

When $TO > 0.5$, no collision occurs between individuals whereas the individual acceleration revise to $t+1$ iteration as,

$$ACC_u^{t+1} = \frac{RD_{best} + Vol_{best} + ACC_{best}}{RD_u^{t+1} + Vol_u^{t+1}} \tag{18}$$

Step 6: Normalize acceleration

The acceleration has to be normalized to evaluate variation proportion that can be mathematically formulated as,

$$ACC_{u-Nor}^{t+1} = w \times \frac{ACC_u^{t+1} - min(ACC)}{max(ACC) + min(ACC)} + L \tag{19}$$

The normalization range of w and L are 0.9 and 0.1 correspondingly, ACC_{u-Nor}^{t+1} signifies the step proportion that each agent changes.

Step 7: Position updation

When $TO \leq 0.5$, the location of u^{th} individual for $t+1$ iteration can be given as,

$$p_u^{t+1} = p_u^t + c_1 \times RAND \times ACC_{u-Nor}^{t+1} \times DDF \times (p_{RAND} - p_u^t) \tag{20}$$

The constant is denoted as c_1 with the value 2, and if $TO > 0.5$, the individuals revise the location as,

$$p_u^{t+1} = p_{best}^{t+1} + K + c_1 \times RAND \times ACC_{u-Nor}^{t+1} \times DDF \times (T \times p_{RAND} - p_u^t) \tag{21}$$

The constant is denoted as c_2 with the value 6, and when T increases, it can be represented as, $T = c_3 \times TO$. The constant is denoted as c_3 with the value 2 and T increases gradually over the time limit $[c_3 \times 0.3, 1]$. To improve exploration and exploitation balance, a new parameter called Z_k is included whereas it can be represented as,

$$Z_k = pi \times 10^{(T \times 100)} \tag{22}$$

The optimal solution obtained after adding a new parameter can be expressed as,

$$p_u^{t+1} = p_{best} \times (DDf + dx) \tag{23}$$

$$dx = pi \times ((1 + Z_k)^{abs(vt)} - 1/Z_k \times sign(vt) \times (UPB_u - LOB_u) \tag{24}$$

$$vt = 2 \times RAND \times (size(p_u^t)) - 1.001 \tag{25}$$

Every individual is assessed using the objective function, and optimal solutions can be attained. The Pseudocode of the TAOA approach is given in Table 3.

Table 3. Pseudocode of TAOA

Algorithm: Feature selection using TAOA

Begin
Input: Extracted features from MVC-based PCA
Output: Optimal solution
Begin
Initialize individual population using equations (9)-(12)
Evaluate the initial population and select an individual as optimal
Set iteration number t=1
While($\mathbf{t \leq t_{max}}()$)
For each individual **u**
Revise volume and density using equations (13) and (14)
Revise **TO** and **DDF** using equations (15) and (16)
If $\mathbf{TO \leq 0.5}$**, then** the exploration phase
Revise the location using equation (21)
Introduce the parameter $\mathbf{Z_k = pi \times 10^{(T \times 100)}}$
Obtain $\mathbf{p_u^{t+1} = p_{best} \times (DDf + dx)}$
End if
End for
Assess every individual and choose one with the finest value
Set $\mathbf{t = t + 1}$
End while
\\ Optimal solution
End

Through the feature selection process, effective features can be selected that reduces the overall dimensionality and reduces time complexity. The selected features are fed into the classification network for effective AD classification.

3.4. Classification using Attn_CNN_LSTM

The process of IoT data classification is undertaken through the Attn_CNN_LSTM classifier model. The proposed model uses the attention layer to enhance the classification performance, pay more attention to the discriminative features, and minimize time consumption. The chief objective of the classification process is to obtain precisely classified AD-based IoT data. The not-part of the experiment, no freeze and freeze classes of AD, are effectively classified using Attn_CNN_LSTM. In the proposed classification model, CNN based LSTM network is utilized, whereas the attention layer is assembled after the pooling layer of CNN, and finally, three different classes are effectively classified. The proposed architecture of Attn_CNN_LSTM is depicted in Figure 2.

3.4.1. Convolutional Layer

In the convolutional layer, the kernel is renovated over the input to create a feature map for the subsequent layers. The kernel gliding produces the mathematical operation called convolution over the input matrix. At every position, element-wise multiplication is undertaken, which is then added to the feature map. The convolution operation tends to be a comprehensive form of a linear process. The convolutional layer outcome can be stated as,

$$q_a^m = L\left(\sum_{b=1}^{N} q_b^{m-1} * y_{ba}^m + z_a^m\right) \qquad (26)$$

From the above expression, the matrix q_b^{m-1}signifies the b^{th}feature map of the previous$(m-1)^{th}$layer, q_a^m denotes the a^{th}feature map of the present m^{th}layer and Nindicates the number of input feature maps. The non-linear function is signified as $L(.)$symbolizing the ReLU function, and the convolution operation is indicated as$*$. The random initialization is sustained over y_{ba}^m, and z_a^m that is set as zero.

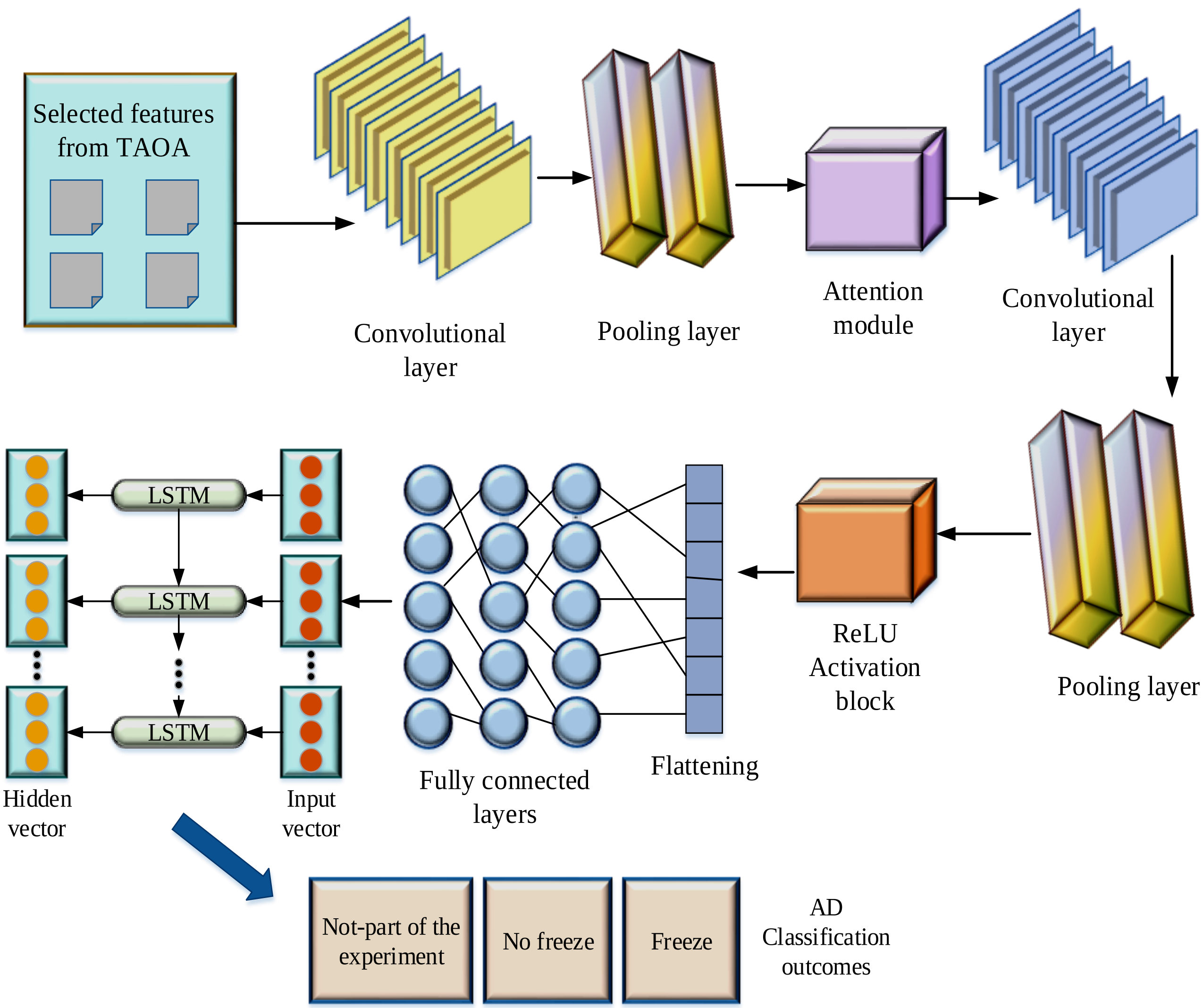


Fig. 2 Schematic representation of the proposed model

3.4.2. ReLU Activation Function

After the convolutional layer, the ReLU activation function is utilized and performs non-linear transformation over input data. ReLU tends to be a piecewise linear function that delivers the output for positive input, or else zero output will be generated.

$$R(s) = Max(0, s) \tag{27}$$

The chief advantage of utilizing the ReLU function is that the neurons cannot be activated simultaneously, which helps to conserve the exponential computation growth in operating the neural network model.

3.4.3. Pooling Layer

The pooling layer helps in the progressive decrement over the feature size design to minimize the parameter quantity and computational difficulty and to handle overfitting issues. The pooling layer diminishes the features generated by a convolution layer and controls the feature resolution to increase steadiness. The pooling layer helps in generating estimated illustrations invariant over smaller input translations.

3.4.4. Attention Layer

In the case of IoT data, not all the features possess the same contribution towards the effective classification of AD. Hence, the attention mechanism is employed to prefer the most significant features by rendering a higher weight value to maximize the significance. The association coefficient between every feature is assessed, whereas the feature vector weights are allocated by assisting the correlation coefficient. The weighted linear integration of feature vectors is combined with the original feature vector to generate a new feature vector demonstration. More attention can be acquired through the utilization of weighted features. The assumption is made that the IoT data comprises of $i$features with the feature length$l$, and the feature vector is signified as$f_{c,d}$. The feature context variables are termed as follows.

$$f_{c,d} = \sum_{a=1, a\neq j}^{l} \beta_{cd,a}\, k_{c,a} \tag{28}$$

From the above equation, β_{cd}denotes the attention weights, $\beta_{cd,a}$represents the correlation coefficient, and that can be expressed as,

$$\beta_{cd,a} = \frac{exp\left(score(k_{cd}, k_{c,a})\right)}{\sum_{d\prime=1, d\prime\neq d}^{l} exp\left(score(k_{cd}, k_{cd\prime})\right)} \tag{29}$$

Greater score values designate that the feature possesses higher weight in the feature vector. The score value can be assessed through,

$$Score(k_{cd}, k_{c,a}) = x_b^T\, tanh\left(w_b k_{cd} + w_i k_{c,a}\right) \tag{30}$$

The training parameters are represented asw_b,$x_b$and w_i, the transpose matrix is signified as T, mapping is done between$k_{cd}$and $x_{u,p}$, varied through matrix mapping of $w_b$andw_i respectively.

3.4.5. Fully Connected Layer

Some final layers are organized by the fully connected layer that grabs the outcome of the pooling layer and extracts the substantial features. The fully connected layer is a major form of the feed-forward neural network, whereas the outcome of every layer is fed over the energized unit of the succeeding layer. The fully connected layer represents that every neuron in the leading layer is associated with every neuron in the second layer.

The major objective of choosing the LSTM network along with CNN is that the learning capability can be superior and more data can be collected for better recognition. The LSTM model is a prolonged version of recurrent neural networks (RNNs). The LSTMs are combined with special units known as memory chunks. The memory chunk in the LSTM model consists of three multiplicative gates and a memory cell. The three basic gates of the LSTM model are given as follows;

- Input gate utilized to fetch the input.
- Forget gate to identify the forgotten data
- Output gate to generate the output

The memory cells keep the system's state in which the three gates guide the activation data flow. The feature vector attained from CNN can be signified as, $\{c_1, c_2, c_3, c_4 \ldots . c_z\}$whereas the hidden vector is indicated as$\{h_1, h_2, h_3, h_4 \ldots . h_z\}$. The basis of LSTM is that a cell state over a single-directional LSTM cell can be evaluated as follows.

$$H = \left[\frac{h_{m-1}}{Q_m}\right] \tag{31}$$

$$R_m = \delta(W_R . H + X_R) \tag{32}$$

$$S_m = \delta(W_S . H + X_S) \tag{33}$$

$$T_m = \delta(W_T . H + X_T) \tag{34}$$

$$O_m = R_m * O_{m-1} + S_m * tanh(W_T . H + X_T) \tag{35}$$

$$p_m = T_m * tanh(\,O_m) \tag{36}$$

From the above equations, the weight matrices are signified asW_R,W_S, W_T and during training, the bias of LSTM cells are signified as X_R, X_S, X_T respectively. The specified terms are represented as the parameters of input, forgot and output gates correspondingly.δ represents the sigmoid function,p_m indicates the input unit over LSTM, element-wise multiplication is indicated as $*$and the hidden vector is signified ash_m. Finally, the non-part of the experiment, no freeze and freeze classes of AD, are effectively classified from the LSTM model.

4. Results and Discussion

The proposed Attn_CNN_LSTM classifier model is examined with diverse stages like pre-processing, feature extraction, feature selection and AD classification. Initially, the collected IoT data are normalized using the ZS-MMAD approach, and the imbalanced data are balanced using the SMOTE algorithm. Next, the pre-processed images are fed into an MVC-based PCA method that performs a feature extraction process. From the extracted features, TAOA selects the optimal features required to improve the classification accuracy. Finally, three diverse classes are classified using the Attn_CNN_LSTM classifier. The performances of the proposed research work will be evaluated using the PYTHON simulation tool, and the outcomes will be analyzed by comparing the proposed model with several existing methodologies. The dataset description, formulation of performance metrics, analysis and comparison are explained in the subsequent sub-sections.

4.1. Acquisition of IoT Data

The Daphnet dataset is specially devised to benchmark automatic approaches to recognize the diverse AD classes from wearable acceleration sensors located on legs and hips. The dataset was collected in the lab, emphasizing the creation of many freeze events. The users conducted three kinds of tasks straight-line walking, walking with several turns and activities of daily living. The Daphnet dataset is the outcome of integration between the neurodynamics and gait laboratory at Wearable Computing Laboratory, ETH Zurich, Switzerland and Tel Aviv Sourasky Medical Center, Israel. The dataset possesses three classes: non-part of the experiment, no freeze and freeze classes. More details regarding IoT acquisition can be found at https://archive.ics.uci.edu/ml/datasets/Daphnet+Freezing+of+Gait.

4.2. Details of Performance Metrics

In this sub-section, various performance evaluation metrics are elaborated to examine the efficacy of the proposed AD classification model. The description of various performance metrics with their equivalent mathematical formulations is explained as follows. The performance metrics, including accuracy, precision, recall, false positive rate (FPR) and F-measure, are described as follows.

4.2.1. Accuracy

The summation of true positive and negative to the overall summation of true and false metrics is termed accuracy. The accuracy metric can be mathematically formulated as follows;

$$A = \frac{T_{pos}+T_{Neg}}{T_{pos}+T_{Neg}+F_{pos}+F_{Neg}} \tag{37}$$

From the above expression, T_{pos} denotes true positive, T_{Neg} represents true negative, F_{pos} signifies false positive and F_{Neg} denotes false negative.

4.2.2. Precision

The portion of significant information from the collected data improves the precision performance. It is also called positive predictive value (PPV). The precision metric can be mathematically formulated as follows;

$$P = \frac{T_{Pos}}{T_{Pos}+F_{Pos}} \tag{38}$$

4.2.3. Recall

The AD classification outcomes are considered to be highly sensitive if the data generates positive cases. It can be defined as;

$$R = \frac{T_{Pos}}{T_{Pos}+F_{Neg}} \tag{39}$$

4.2.4. False Positive Rate

The ratio between the quantity of negative outcomes that are wrongly categorized as positive is analyzed in FPR, and that can be formulated as,

$$FPR = \frac{F_{Pos}}{F_{Pos}+T_{Neg}} \tag{40}$$

4.2.5. F-Measure

The combination of precision and recall to a single value is termed an F1 measure. The mathematical formulation can be given as follows;

$$FM = 2\frac{PPV \times TPR}{PPV+TPR} \tag{41}$$

4.3. Comparison with Baseline Models

The proposed Attn_CNN_LSTM classifier model includes incorporating diverse existing approaches to generate an ecosystem of Alzheimer's patients that can cooperate in daily activities. The performances of the proposed classifier model are compared with the existing methods to analyze the results in the case of the Daphnet dataset. The existing models like Bayes Net (BN), Naïve Bayes (NB), logistic, simple logistic (SL), Decision tree (DL) and RNN are compared with the proposed classifier model. The performances are analyzed by considering the metrics like accuracy, precision, recall, FPR and F-measure.

Table 4 represents the proposed performance outcomes in terms of significant performance metrics.

Table 4. Comparison of proposed and existing approaches [28]

Methods	Performance outcomes (%)				
	CCI	Precision	F1-Score	Recall	FPR
BN	72.8	80	74.2	72.9	20.3
NB	77.2	75	70.9	72.3	26.7
Logistic	74.1	75	71.2	74.2	27.6
SL	74.3	74	70.8	74.3	28.1
DT	82.8	80	81	82.9	16.4
RNN	88.9	83	84	88.6	86.6
Proposed	**95.68**	**93.53**	**93.53**	**93.53**	**3.23**

The above-given table exemplifies the relative examination of the proposed classifier model with existing approaches for the Daphnet dataset. A clear investigation can be made that the proposed method achieves better performance outcomes than existing approaches. Figure 3 shows the graphical representation of CCI performance in the case of proposed and existing methods.

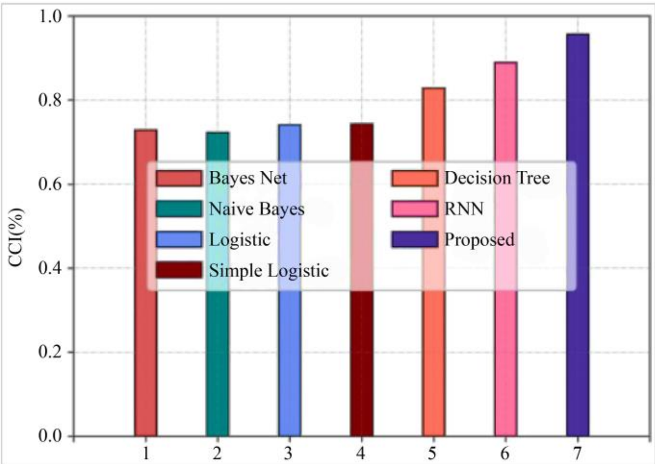


Fig. 3 CCI performance

From the above graphical comparison, a justification can be clearly made that the accuracy or correctly classified instances (CCI) of the proposed model in AD classification using the Attn_CNN_LSTM classifier model is 95.68%.

Better accuracy is attained due to the effectual feature selection process by eradicating unsolicited features and enhancing training capability. Minimal error possibilities are found because of the effective application of solicited features.

The IoT data collected from the Daphnet dataset are provided as the input, whereas improved classification accuracy can be gathered.

The CCI or Accuracy performance is compared with existing methods like BN, NB, Logistic, SL, DT and RNN that have gained inferior performance because of certain demerits like less robustness and larger accumulation of features, whereas better performance is attained in the case of the proposed model.

The accuracy in classifying not-part of the experiment is obtained as 95.71%, no freeze class as 95.60% and freeze class as 95.74%. Figure 4 (a)-(d) demonstrates the performance of proposed and existing models regarding diverse metrics.

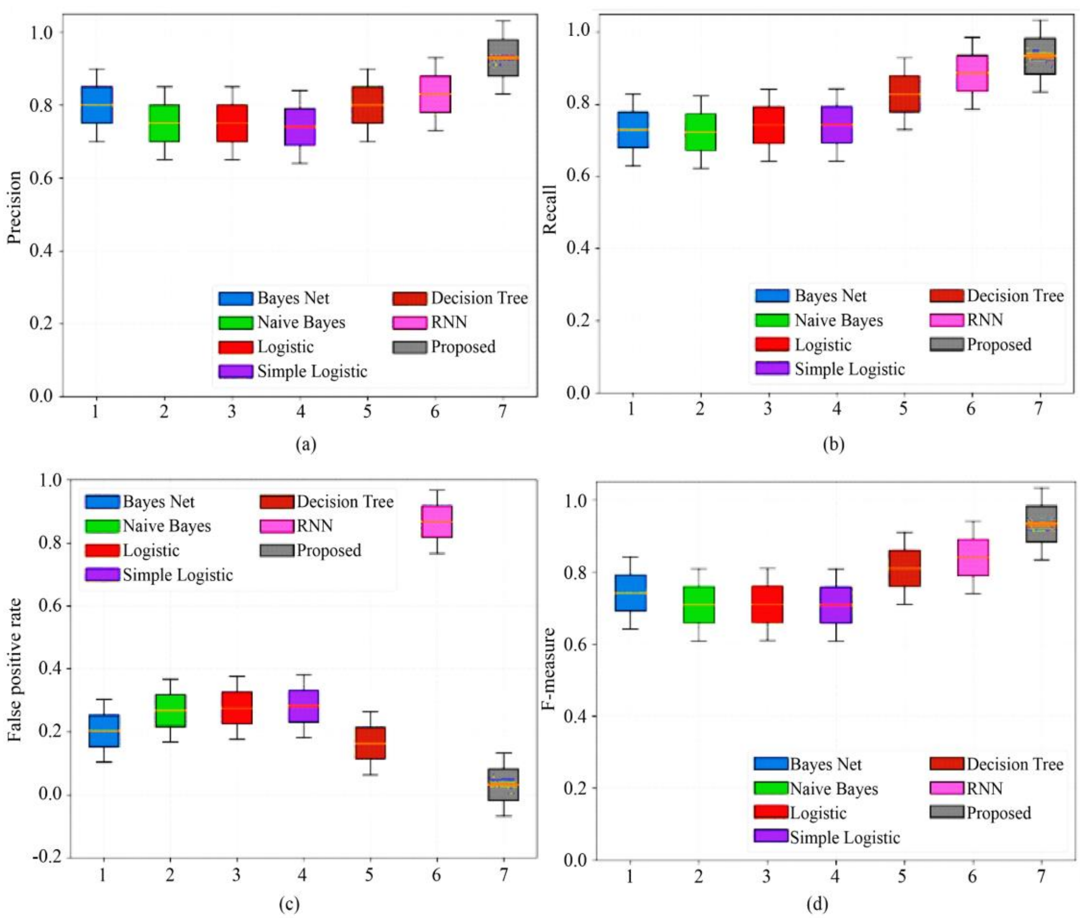


Fig. 4 Performance comparison (a) Precision (b) Recall (c) FPR (d) F-measure

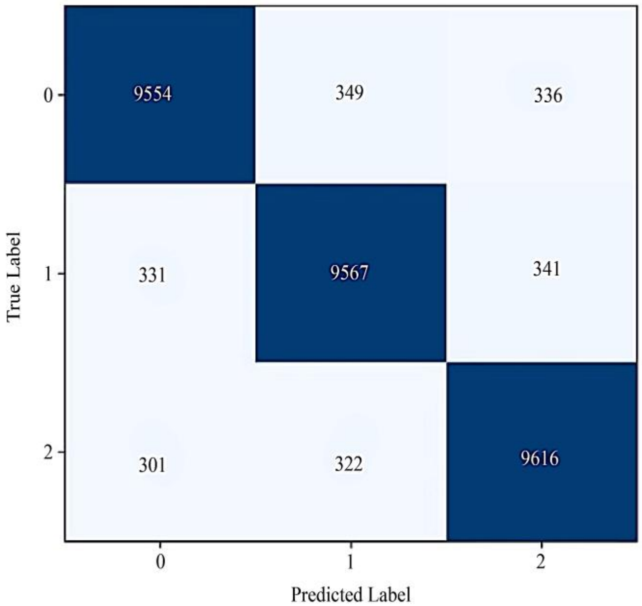


Fig. 5 Confusion matrix

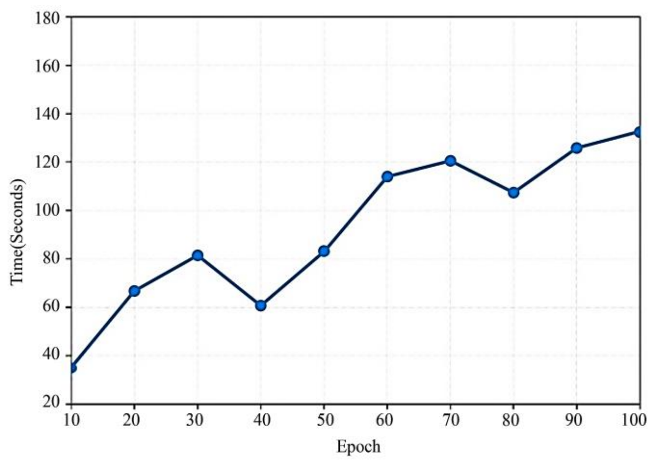


Fig. 6 Time consumption Vs Epoch size

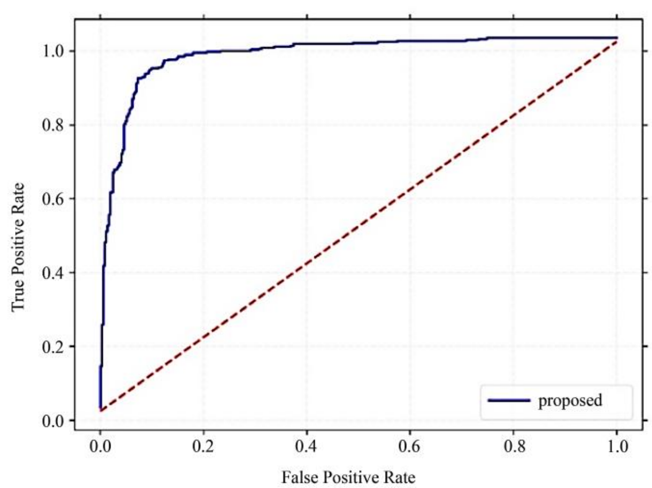


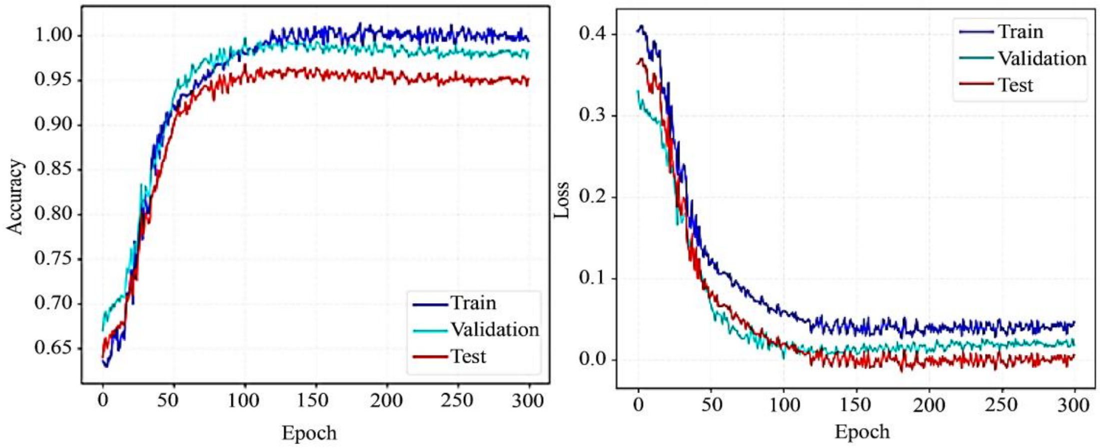
Fig. 7 ROC analysis

From the validated figure, a noticeable justification can be made that the proposed model performs better than existing IoT data classification methods. The precision performance in classifying IoT data is 93.53% by the proposed model, whereas the existing models like BN obtained 80%, NB has attained 75%, logistic is 75%, SL is 74%, DT is 80%, and RNN has attained 83%. The proposed performance of recall is obtained to be 93.53% whereas the existing BN has obtained 72.9%, NB has attained 72.3%, logistic as 74.2%, SL as 74.3%, DT as 82.9%, and RNN has attained 88.6% in which the existing methods fails to render good outcomes.

Similarly, the performance of the F1 score of the proposed model is attained to be 93.53%, whereas the existing models are found inferior in AD classification compared to the proposed approach. The proposed model performs better than existing techniques due to implementing a well-organized Attn_CNN_LSTM classifier model. The IoT data are provided as the input, and medical data classifications are made more exact through the proposed model. On account of FPR performance, lesser rates are obtained by the proposed model at 3.23%, whereas the existing models obtain greater rates of FPR that adversely degrades the overall performance. The existing methods attained fewer performance results than the proposed model due to higher feature dimensionality, increased error, less flexibility and low convergence rate. Figure 5 validates the confusion matrix of the proposed model on account of three classes.

The major intention of the proposed Attn_CNN_LSTM classifier model is to classify three different classes, including not-part of the experiment, freeze and no-freeze classes. Here the IoT data collected from the Daphnet dataset is considered for classifying the three diverse classes of AD. An obvious examination can be made from the above figure that the proposed model perfectly classifies the AD stages with better accuracy rates. Class' 0' represents a non-part of the experiment, '1' signifies freeze, and '2' represents the no-freeze class. 9554' 0' classes are accurately predicted, whereas 331 classes are wrongly predicted as '1' and 301 classes as '2'. 9567 classes are accurately predicted as '1', whereas 349 classes are wrongly predicted as '0' and 322 classes are wrongly predicted as '2'. 9616 classes are accurately predicted as'2' whereas 336 classes are wrongly predicted as '0' and 341 classes as '1'. The three classes are classified with minimalized error possibilities, so the proposed model's accuracy is widely enhanced. Figure 6 demonstrates the time taken by the proposed model by varying the epoch size from 10 to 100.

The time taken by the proposed Attn_CNN_LSTM classifier model is measured in terms of seconds. Time is significant in the classification model because it is considered a non-significant approach if the time consumption to detect AD outcomes is high. If the results are attained within a small period of time, immediate actions can proceed further.



(a) (b)

Fig. 8 Performance outcomes (a) Accuracy curve (b) Loss curve

The proposed Attn_CNN_LSTM classifier model attained effective prediction accuracy in a shorter computational time. The time taken by the proposed model is obtained to be 132.43 for 100 epochs, whereas 60.71 seconds for 40 epochs and 107.26 seconds for 80 epochs have been obtained correspondingly. When the epoch size gets increased, the time taken by the classifier model also gets maximized.

Figure 7 illustrates the Receiver operating characteristic (ROC) performance analysis of the proposed model in AD classification. The ROC is analyzed in terms of FPR and TPR, whereas the optimal cut-off displays the maximum TPR or sensitivity with minimum FPR or specificity. The ROC curves are frequently examined to indicate the trade-off between TPR and FPR. It represents the efficiency of AD classification outcomes with minimizing error and time consumption. The ROC curve also signifies the degree of ability in differentiating the classes. A higher rate of ROC signifies better performance of AD classification. From the figure, it can be clearly noticed that the ROC analysis delivered superior outcomes in the proposed model.

4.4. Training and Testing Evaluation of Accuracy-Loss

The accuracy and loss of the proposed Attn_CNN_LSTM classifier model are analyzed with training and testing data. In the proposed research work on AD classification, 70% of data is used for training, 15% for testing and 15% for validation. Figure 8 (a)-(b) portrays the accuracy and loss performance attained during diverse stages of the proposed model.

By changing the epoch size from 0-300, the accuracy and loss performance of the proposed Attn_CNN_LSTM classifier model is measured. The accuracy assessed for testing, validation and training is similar to the above graphical statement. The accuracy increases with increased epoch size, whereas the loss decreases with increased epoch size. If the epoch size is 50, the proposed method obtains a training, testing and validation accuracy in the range between 85 to 90% consecutively. If the epoch size is 150, the proposed model generates an accuracy in the range of 93 to 98%. When the epoch size is increased to 300, 95 to 100% accuracy is attained.

Moreover, from the figure, it is obvious that the proposed model attains maximum accuracy. The training, validation and testing loss is examined for the proposed model, and the network has been trained for 300 epochs. If the epoch size is 50, the model attains a loss between 0.05-0.15. If the epoch size increases to 300, the model obtains a loss of 0.01-0.07. The proposed model obtained minimal losses due to effective data training through the Attn_CNN_LSTM classifier model.

5. Conclusion

One of the most threatening diseases among people in recent days is AD, where severe complexity will be faced if there is a lack of diagnosis at earlier stages. Attn_CNN_LSTM is employed in the proposed research work for effective AD classification stages. Initially, the data are collected from the Daphnet dataset and pre-processed using data normalization and balancing. The IoT data are normalized using the ZS-MMAD technique, and data balancing is performed using SMOTE process. In order to minimize the dimensionality of features and computational time, MVC-based PCA is presented as a feature extraction process. TAOA is then used to select optimal features relevant to improving classification accuracy and minimizing feature complexity. Finally, the non-part of the experiment, Experiment and Freeze classes of AD, are efficiently classified through Attn_CNN_LSTM. The performance of the proposed approach is proved to be better compared with diverse existing approaches. An accuracy of 95.68% is attained in the AD classification, and the simulations are performed using the PYTHON tool. In the future, the proposed work can be extended further by considering multimodal data like images and speech as input. Also, prominent methods will be deployed to enhance the overall performance, and more suitable features will be used to improve the classification accuracy.

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