International Journal of Communication Networks and Information Security
ISSN: 2073-607X, 2076-0930
*Volume **14** Issue **02 Year 2022** Page **53:65***

Cognitive Based Attention Deficit Hyperactivity Disorder Detection with Ability Assessment Using Auto Encoder Based Hidden Markov Model

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Article History

Received: 11 Feb 2022
Revised: 25 May 2022
Accepted: 11 June 2022

Abstract

Attention deficit hyperactivity disorder (ADHD) is a frequent Neuro-generative mental disorder. It can persist in adulthood and be expressed as a cognitive complaint. Behavioural analysis of ADHD consumes more time. This is a multi-informant complex procedure due to the overlaps in symptomatology which is the cause for delay in diagnosis and treatment. Dur to these behavioural consequences and various causes, no single test is utilized till now for diagnosing this disorder. Hence, a diagnosing model of ADHD based on Continuous Ability Assessment Test (CAAT) can enhance and balance behavioural assessment. The objective behind this study is to use a deep learning based model with CAAT for predicting ADHD. The proposed Auto Encoder Based Hidden Markov Model (AE-HMM) produces low-dimensional features of brain structures, and a novel Pearson Correlation Coefficient (PCC) is employed for normalizing these features in order to minimize batch effects over populations and datasets. This goal is consistently achieved and thus the proposed model outperforms few standard approaches which are considered like CogniLearn and 3-D Convolutional Neural Networks (3DCNN). It is found that the proposed AE-HMM method achieves 93.68% of accuracy, 90.66% of sensitivity, 87.72% of specificity, 87.78% of F1-score and 74.22% of kappa score.

Keywords-Neurogenerative disease, cognitive, ability assessment, Hidden Markov Model (HMM), Feature extraction.

1. Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is classified based on the symptoms of lack of concentration due to age factor, impulsivity and hyperactivity [1]. ADHD is a common widespread disorder found in childhood at about 7% of problems is carried on to adulthood and results in poor social and academic outcomes [2]. From the deep investigation on ADHD, it is revealed that there is a deficit in subcortical regions like basal ganglia and insula. From the vast analysis of subcortical structural imaging, it is found that around 23 sites which includes about 1713 ADHD patients experienced reductions besides basal ganglia [3]. Abnormalities in the front ventromedial regions are more and it is evident that there is a delay in cortical thickness maturation in temporal, frontal and parietal regions [4]. Besides structural deficits in Gray matter region, even the white matter region are damaged due to the disorder [5]. The focus of Psychologists is mainly on psychotherapy and providing treatment towards emotional and mental suffering of patients. Moreover, psychological testing is conducted as it is essential to access the mental state of the person and accordingly determine the effective treatment. The prediction system helps these psychologists while performing this test and even in the prediction of mental health of people [6]. Psychiatrists and psychologists work together to treat behavioural as well as clinical perspective symptoms. Various factors which influence the mental health of people are pressure in workplace, globalization, competition while studying etc. Nowadays, ADHD in children are diagnosed from the information given by parents, accessing children's behaviour and rating scales at clinics and neuropsychological tests [7]. Commonly used clinical rating scales to evaluate ADHD are Parent rating scale (PSQ) and Child Behaviour Checklist (CBCL) [8]. The recent focus is on developing objective tools for evaluation and managing ADHD [9]. Integrated Visual and Auditory Continuous Performance Testing (IVA-CPT) has the ability to discriminate ADHD children accurately. Right now, no standard tool is available for analysing the results of different tools used in diagnosing ADHD [10]. Hence, clinical rating scales and neuropsychological tests are analysed by clinicians based on their ability and experience. This work focuses in,

- Construction of Auto Encoder Based Hidden Markov Model (AE-HMM) to obtain low-dimensional volumetric features from pre-defined atlas brain structures, and a novel Pearson Correlation Coefficient (PCC) for normalizing these features.
- Development of Continuous Ability Assessment Test (CAAT) for the prediction of ADHD.

The organization of paper is as: Section 1 presents the background of Attention Deficit Hyperactivity Disorder (ADHD), cognitive assessment and the application of neural network in ADHD prediction along with motivation and contribution. In section 2, the existing traditional methods for cognitive assessment in ADHD are discussed. Section 3 explains the proposed AE-HMM architecture with feature extraction and ability assessment concept. In section 4, the experimental analysis is described. Finally conclusion and future work is given in section 5.

2. Related Works

In [11] CogniLearn, performs automatic capturing and analysing of user motion using HTKS game and evaluations are made in detail with standard computer vision and deep learning approaches for recognizing the activities. The intuitive and special user interface supported this system assisting human experts for cross-validating and refining the process of diagnosis. In [12], gradient-weighted class activation mapping (Grad-CAM) approach based on CNN and visualization methods was used to identify spatial-frequency abnormalities with EEGs of children affected with ADHD. Totally, 50 ADHD children and 57 controls were employed. In [13], a multichannel deep neural network (mcDNN) classification system was developed based on multiscale brain functional data and personal characteristic data (PCD) as integrated features to identify ADHD. In [14], a novel computer aided diagnosis (CAD) model was introduced employing deep learning techniques for the classification of EEG signal of Healthy and ADHD children. These ADHD children were classified as Combined (ADHD-C) and Inattentive ADHD (ADHD-I). Further, DCNN model was involved in extracting and classifying spatial and frequency features from EEG signal. In [15] , the model used involved two 3D-CNN with different structures which extracts features from functional MRI (fMRI) data and structural MRI (sMRI) data of the subjects. Then their outcomes are integrated using summation induced procedure which in turn was given as input to the fully connected neural network and produces binary classification prediction. In [16], a deep learning technique was introduced to identify ADHD integrating EEG-based brain network with CNN. The order of the channels were rearranged using a novel connectivity matrix which involved convolution operation 13 hand-crafted measures of brain network along with correlations of deep features of CNN were analysed.

When comparing the above mentioned networks with the related cognitive domains, the use of existing Turing Test can be considered to evaluate human cognition. The success of the various Turing test depend only on the quality of classification technique with computer's intelligence which motivated the formulation of the proposed AEHMM method discussed in the forthcoming section

3. System Model

The proposed AEHMM model comprises of three major steps namely feature extraction, classification and assessment of subjects as healthy or cognitively impaired. The focus is on obtaining optimal and sustainable solution to discriminate ADHD subjects at different stages as shown in figure-1.

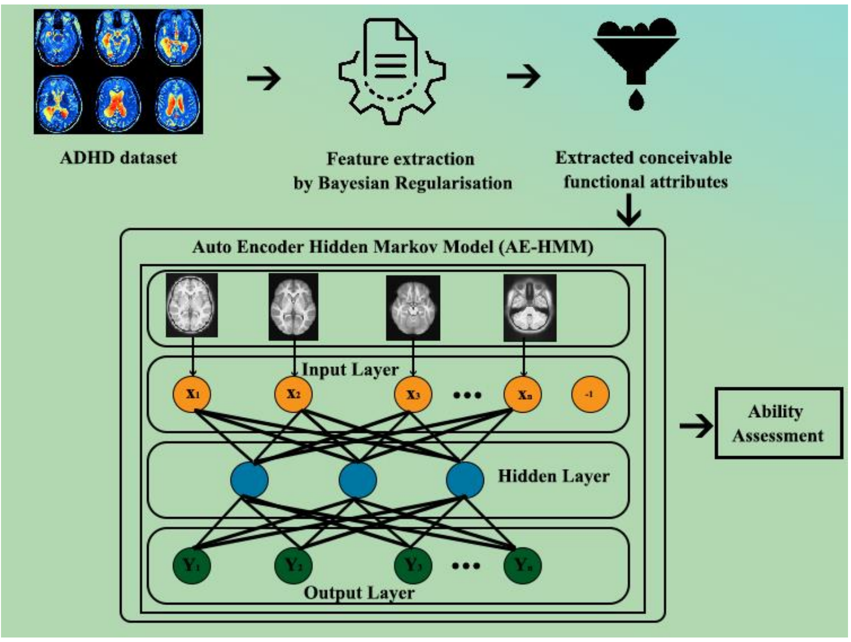

Figure-1 *System architecture for ADHD detection and ability assessment*

Initially, features are potentially extracted from the sensing dataset. Next, AE-HMM produces low-dimensional volumetric features from pre-defined atlas brain structures and the trained classifier predicts the cognitive health status of a person. Finally, Continuous Ability Assessment Test (CAAT) assists to predict the score of the patient affected with ADHD.

3.1 Dataset description

For lack of concentration and impulsivity related to ADHD, the most popular objective measure is continuous performance test (CPT) [17]. This test generally includes a sequential representation of visual or auditory non-target and target stimuli (a series of numbers/letters, numbers, letters, or geometric figures). Lack of concentration is measured when target stimuli ("omission error") are not responded. Impulsivity is measured when there is a response to non-target stimuli ("commission error"). For the CPT response, few other standard measures are total appropriate responses, response time (RT) and its variations. There are 458 children who are between the age group 6–12 out of which 41% were girls (191) and 59% were boys (267). Among them, 213 were detected as ADHD children, and others were normally developed. Age variations were not identified among ADHD and non-ADHD category. The rate of boys was considerably more in ADHD (67%) than non-ADHD (51%).

3.2 Feature extraction by Bayesian Regularisation

When a time series analysis was used, 783 features were engineered totally. While garnered intuition was used on the ometric data, 22 custom features were engineered. Features consist of Fourier transform metrics, aggregated linear trends, approximate entropy, energy spectral density, and standard statistical values of attribute-sizes like mean, median, standard deviation, and variance obtained at different time intervals. For every trial, the features were obtained which were then finally averaged. They were grouped using the patient ID and thus, for every patient, a systematic detailed feature space was provided. Prior to analysis, cubic spline interpolation was used to estimate the missing values. The trials which exhibited 80% and more missing data were not included for analysis [18]. Assume that PT1−T2 indicates the time interval in ms from time T1 to T2 and PS denotes the probe presentation at 5000 ms mark. For the given T0 and P0 which represent the starting timestamp and attribute size respectively, the dilation velocity Vi for the attribute size Pi at any given timestamp Ti is given as indicated in equation (1),

$$Vi = \frac{Pi-Po}{Ti-To} \tag{1}$$

Several reasonable functional attributes for simple activities are extracted using Bayesian Regularisation which includes activity, duration, total sensors used and their events.

- Activity: This is a Boolean feature which informs if the participant completed the activity
- Duration: This is the total time taken by the activity for completion.
- Sensor Count: This is the count of using a certain sensor in an activity.
- Sensor Events: This gives the count of unique sensor events performed in an activity.

3.3 Construction of an Auto Encoder Hidden Markov Model (AE-HMM)

Auto Encoder (AE) comprises of an encoder and decoder neural network. The former is responsible to transform input data x into latent representation q(zjx) while the latter regenerates the input sequence from latent distribution by learning p(xjz) as shown in figure 2. For the dataset X = fx(i),Gni=1,as AE is a generative model, model evidence is used to evaluated it. However, the model evidence p θ(X) is not computationally tractable.

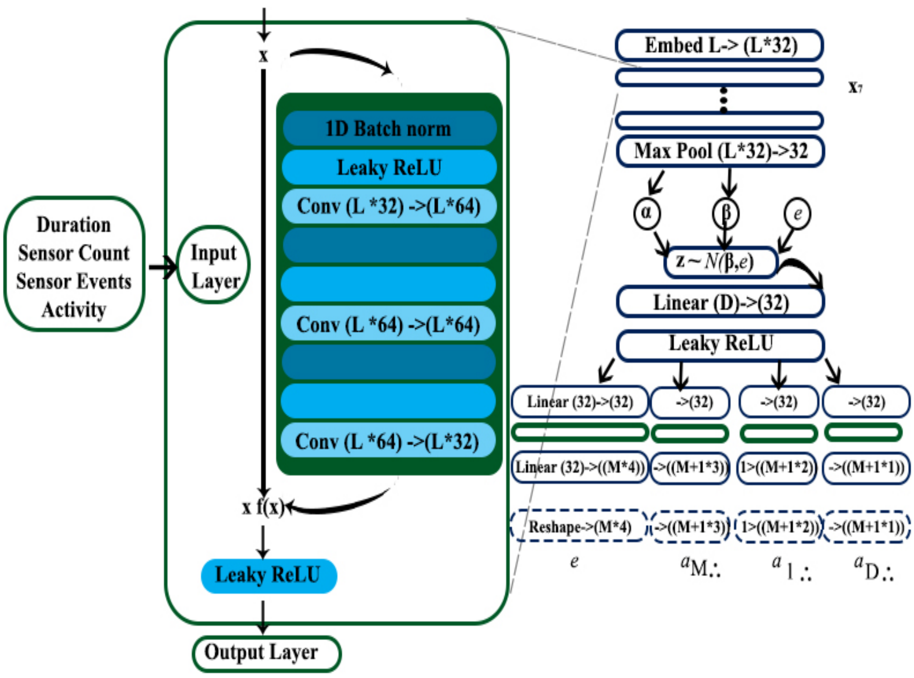

Figure-2 *Overall architecture of Auto Encoder with Hidden Markov Model (AE-HMM)*

On the other hand, Evidence Lower BOund (ELBO) L(θ;α;X) can be maximized to estimate the way in which dataset is described by the model when Jensen's inequality is used [19] which is given as indicated in equations (2) and (3),

$$\log \theta(x) \geq L(\theta;\alpha;X)=\sum_{i=1}^{N} L(\theta;\alpha;X)i \quad (2)$$

where,

$$L(\theta;\alpha;X)i = -Dkl(q\alpha(z,x(i))p\theta(z))+E_{q\theta(z,xi)}[\log p\theta(xi,z) \quad (3)$$

where Dkl(qα) represents Kullback Leibler divergence between the distributions p and q. The two terms of the above equation represents the regularization and reconstruction error respectively. This reconstruction error can be modelled to be appropriate for the problem which determines the latent space structure. To model insertions and deletions, profile hidden Markov Model (pHMM) is used as decoder in AE. HMM produces the output by switching from one state to other probabilistically. The pHMM consists of three states namely match (M), insertion (I), and deletion (D) states. Every state produces certain outputs which represent multiple sequence alignments. M is highly feasible to send out a character particularly, I have an equal chance, and D gives out a null character always. This probability parameter is termed as emission probability. The other one is the transition probability which describes the possible transition from one state to other. In pHMM, emission probability eS(c) is defined as the probability of output character c from state S defined as p(cjS), and transition probability aS;S0 is the probability of the state changing from S to S0 given as p(S0jS), Here, state transition is based on the prior state. The sequence probability p(x) [20] is given by Markov chain rule as indicated in equation (4):

$$P(x) = \sum_{\pi} p(x,\pi) = p(x0:l+1,\pi last = M(m+1) \quad (4)$$

The forward approach includes a forward variable which is given as fj(i)=p(x0:iπlast=sj) and the probability can be periodically estimated as indicated in equations (5), (6) and (7),

$$Fk(l)m=eMk(xl)\sum_{S\in\{m,i,d\}} aSK-1,mK,fs(k-1)(l-1) \quad (5)$$

$$Fk(l)i=Ei(Xi)\sum_{s\in\{M,I\}}^{n} aSK-1,MK,fs(l-1) \quad (6)$$

$$Fk(l)d=\sum_{s\in\{M,d\}}^{n} aSK-1,MK,fs(l) \quad (7)$$

Back propagation as a loss function is employed to train AE-HMM where continuous learning is allowed. By this, probability meaningless transitions into deletion states can be reduced. The probability of categorical sampled variable p ={pk} from a Dirichlet distribution parameter α={αk} is given as indicated in equation (8)

$$Dir(p/\alpha)=\frac{\prod_{k-1}^{k}\alpha k}{\sum_{k-1}^{k}\alpha k}\sqrt{pk.ak-1} \quad (8)$$

The sum of the ratio of log-odds of training probability from M at position i is termed as regularization which is defined as in equation (9)

$$Lm(pi,e,r\} = \log(\frac{(2+wm)(1+wm)}{2} \quad (9)$$

Here the transition probability pi is [aMi-1,Mi aMi-1Ii, aMi-1, Di], and induction weight wm is represented by the parameter α(wm) = [1+wm]. at a specific round R, this loss is made zero by sewtting wm to 4(1 + e/R), where training epoch is represented by e . For each training sample,D nonlinear features are constructed by the auto encoder. The linear dependencies of the abstract representation of each sample is calculated by utilizing the Pearson Correlation Coefficient (PCC) which is described below for two samples A and B as indicated in equation (10):

$$R(A,B)=\frac{1}{d-1}\sum_{i=1}^{d}\left(\frac{Ai-\partial A}{\theta A}\right).\left(\frac{Bi-\partial B}{\theta B}\right) \quad (10)$$

here mean and the standard deviation of sample A is given as μA and σA respectively, and μB and σB are of sample B. This vector is normalized between zero and one which is defined as the criteria for predicting the degradation starting point and consequently determining the health status of the system. Different learning schemes like sample delete as well as reserve, neuron growth, and updating parameter along with self-regulated thresholds are involved in Meta-cognitive component for modelling the dynamics of that component which assists in monitoring and controlling the component. This component involves knowledge measures namely maximum hinge loss (Et), predicted class label (bc t), class-wise significance (ψc) and confidence of classifier (pˆ(c t |x t)) in the new sample during training. These learning strategies are specialized to improve the simplification of classification.

Input: ADHD Dataset D = {(x1 , y1),(x2, y2), . . . ,(xm, ym)};
Output: Classified data
Learning (L)= L1 , L2, . . . , Ln;
Initiate training (t) process
for t = 1, . . . , T:
ht = Lt(D)
end;
D0 = φ;
for i = 1, . . . , m:
for t = 1, . . . , T:
zit = hi (xi)
D0 = D0 ∪{((zI1 , zi2 , . . . , zT), yi)}
end;
prediction (p)←vote(D0,D1,D2….Dn)
folding(f)←10
Calibration of inequality (eq)
Eq←L(θ;α;X)
Occurance of chain process Fk(l)m, Fk(l)I and Fk(l)d
Calculation of Pearson correlation coefficient (PCC)= R(A,B)
End

3.4 Ability assessment

The cognitive Ability assessment measures involved in this study is done by using Continuous Ability Assessment Test (CAAT). For example, a boy of 12 years old who struggled in school was given CNS Vital Signs VSX BRIEF- CORE Clinical Battery. His score was below average in 5 cognitive domains out of 12. Table 1 summarizes the ability assessment skill using Continuous Ability Assessment Test (CAAT)

Table-1 Continuous Ability Assessment Test (CAAT) and score

Ability assessment skills	**score**
Phonological Short-term Memory	Low level
Focus	Average level
Contextual Memory	Low level
Divided Attention	Very low level
Inhibition	Average level
Hand-eye Coordination	Very low level
Naming	Average level
Planning	low level
Recognition	Average level
Response Time	Very low level
Spatial Perception	low level
Visual Perception	Average level

The Neuropsychic Questionnaire with ability assessment is not a diagnostic tool. The obtained outcome was interpreted by a skilled clinician during clinical investigation. It is not necessary that the patient has a specific condition; it is just found that he has more severe symptoms. On the contrary, a patient having secured low score just means that no symptoms are reported under that specific condition during the particular time interval. However, patients exhibit conditions and few over-state their difficulty while some under-state them.

4. Performance Analysis

The experimental result is carried out and the parameters used for analysis are accuracy, sensitivity, specificity, f1-score and kappa score. These parameters are compared with two standard methods such as CogniLearn and 3-D Convolutional Neural Networks (3DCNN) with the proposed Auto Encoder based Hidden Markov Model (AE-HMM)

Accuracy presents the ability of the overall prediction produced by the model. True positive (TP) and true negative (TN) provides the capability of predicting the absence and presence of attack. False positive (FP) and false negative (FN) presents the false predictions made by the used model. The formula for accuracy is given as in equation (11):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

Table 2 presents the comparative analysis of accuracy between existing CogniLearn, 3DCNN methods and proposed AE-HMM method.

Table 2. *Comparison for Accuracy*

Number of epochs	**CogniLearn [11]**	**3DCNN [15]**	**AE-HMM [proposed]**
100	88.1	85.5	90
200	89.6	89.2	91.6
300	92.8	92.6	94.5
400	93.2	94.5	95.4
500	94.5	96	96.9

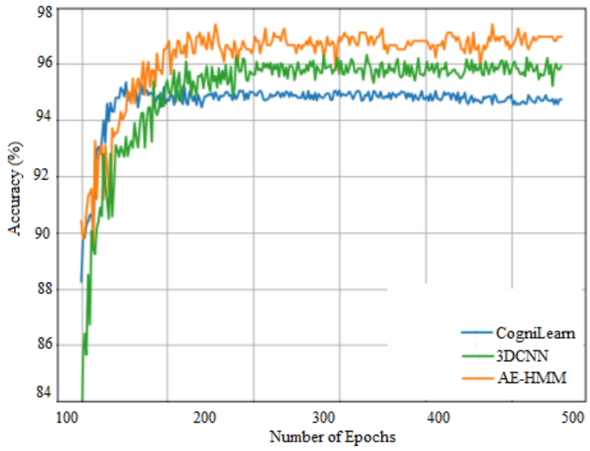

Figure 3. *Comparison of accuracy*

Figure 3 illustrates the comparison of accuracy between existing CogniLearn, 3DCNN methods and proposed AE-HMM method where X axis shows the number of epochs used for analysis and Y axis shows the accuracy values obtained in percentage. When compared, existing CogniLearn and 3DCNN methods achieve 91.64% and 91.56% of accuracy respectively while the proposed AE-HMM method achieves 93.68% of accuracy which is 2.04% better than CogniLearn and 2.12% better than 3DCNN method.

Sensitivity estimates the efficiency of the classification model. It is the probability of positive prediction if disease is identified and is also termed as True Positive Rate (TPR) which is estimated as in equation (12):

$$Sensitivity \ = \frac{TP}{TP+FP} \tag{12}$$

Table 3 shows the comparison of sensitivity between existing CogniLearn, 3DCNN methods and proposed AE-HMM method.

Table 3. Comparison for sensitivity

Number of epochs	CogniLearn [11]	3D CNN [15]	AE-HMM [proposed]
100	79.5	77.2	87.1
200	79.6	79.5	89.5
300	81.5	84.6	90.6
400	83.6	86.9	91.9
500	87.2	91.6	94.2

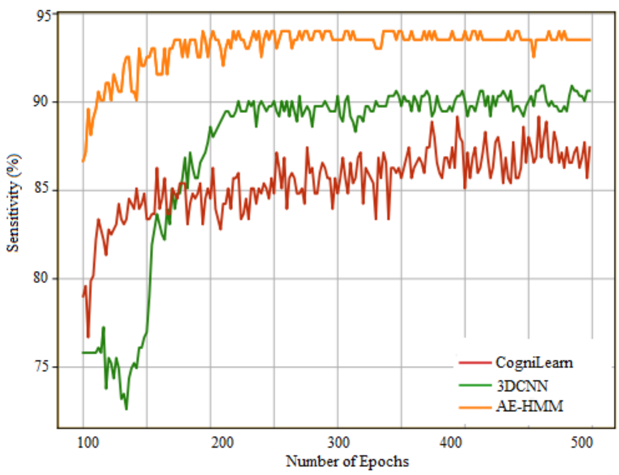

Figure 4. *Comparison of sensitivity*

Figure 4 illustrates the comparison of sensitivity between existing CogniLearn, 3DCNN methods and proposed AE-HMM method where X axis shows the number of epochs used for analysis and Y axis shows the sensitivity values obtained in percentage. When compared, existing CogniLearn and 3DCNN methods achieve 82.28% and 83.96% of sensitivity respectively while the proposed AE-HMM method achieves 90.66% of sensitivity which is 7.42% better than CogniLearn and 7.3% better than 3DCNN method.

Specificity is the probability of true negatives aptly identified and is also termed as True Negative Rate (TNR). The formula for specificity is given as in equation (13):

$$Specificity = \frac{TP}{TP+FN} \tag{13}$$

Table 4 shows the comparison of specificity between existing CogniLearn, 3D CNN methods and proposed AE-HMM method.

Table 4. *Comparison for specificity*

Number of epochs	**CogniLearn [11]**	**3D CNN [15]**	**AE-HMM [proposed]**
100	83.2	83.5	83.9
200	83.8	84.6	85.6
300	85.1	86.4	88.4
400	85.9	88.5	89.6
500	86.3	90.1	91.1

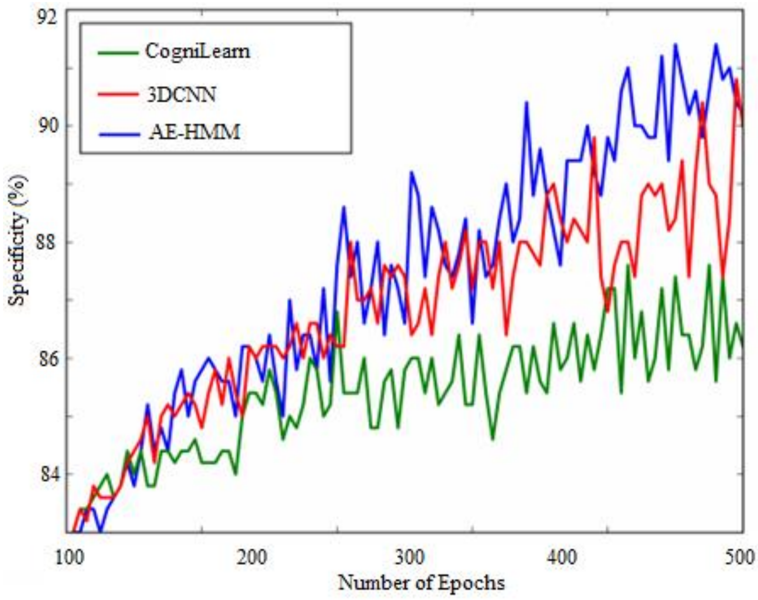

Figure 5. *Comparison of specificity*

The figure 5 shows the comparison of specificity between existing CogniLearn, 3DCNN methods and proposed AE-HMM method where X axis shows the number of epochs used for analysis and Y axis shows the sensitivity values obtained in percentage. When compared, existing CogniLearn and 3DCNN methods achieve 84.86% and 86.62% of specificity respectively while the proposed AE-HMM method achieves 87.72% of specificity which is 3.14% better than CogniLearn and 1.1% better than 3DCNN method.

F1-score is utilized to determine the prediction performance. It is the weighted average of precision and recall. The value of 1 determines the best while 0 the worst. f1-score does not consider TNs and is calculated as in equation (14):

$$f1 - Score = \frac{2*P*R}{P+R} \tag{14}$$

Table 5 shows the comparison of f1-score between existing CogniLearn, 3D CNN methods and proposed AE-HMM method.

Table 5. *Comparison for F1-score*

Number of epochs	CogniLearn [11]	3D CNN [15]	AE-HMM [proposed]
100	82.1	83.9	84.5
200	83.6	84.6	87.9
300	84.5	85.4	88.1
400	86.4	86.9	88.5
500	88.1	89.6	89.9

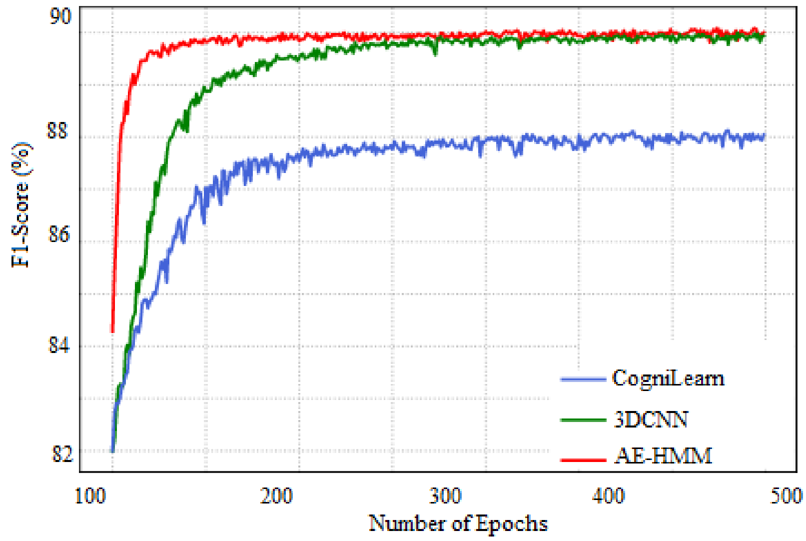

Figure 6. *Comparison of F1-score*

The figure 6 presents the comparative analysis of F1-score between existing CogniLearn, 3DCNN methods and proposed AE-HMM method where X axis shows the number of epochs used for analysis and Y axis shows the f1-score values obtained in percentage. When compared, existing CogniLearn and 3DCNN methods achieve 84.94% and 86.08% of F1-score respectively while the proposed AE-HMM method achieves 87.78% of F1-score which is 3.24% better than CogniLearn and 1.7% better than 3DCNN method.

kappa score is employed to ensure inter rate reliability which represents the correctness of the data collected which represents the variables measured.

Table 6 shows the comparison of kappa score between existing CogniLearn, 3D CNN methods and proposed AE-HMM method.

Table 6. *Comparison for kappa score*

Number of epochs	CogniLearn [11]	3D CNN [15]	AE-HMM [proposed]
100	68.8	69.9	70.2
200	68.9	71.1	71.5
300	69.2	71.3	73.6
400	69.6	71.4	75.9
500	69.8	71.5	79.9

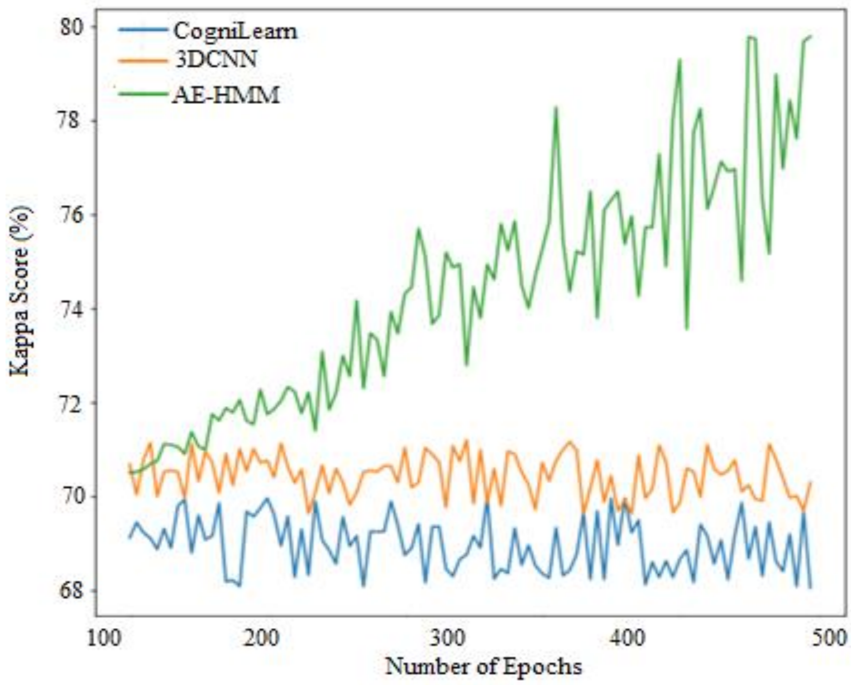

Figure 7. *Comparison of kappa score*

The figure 7 shows the comparison of kappa score between existing CogniLearn, 3DCNN methods and proposed AE-HMM method where X axis shows the number of epochs used for analysis and Y axis shows the kappa score values obtained in percentage. When compared, existing CogniLearn and 3DCNN methods achieve 69.26% and 71.04% of kappa score respectively while the proposed AE-HMM method achieves 74.22% of kappa score which is 5.24% better than CogniLearn and 3.22% better than 3DCNN method.
Table 9 presents the overall comparison for various parameters between existing existing CogniLearn, 3D CNN methods and proposed AE-HMM method.

Table 9. *Overall comparison of existing and proposed methods*

Parameters	**CogniLearn [11]**	**3D CNN[15]**	**AE-HMM [proposed]**
Accuracy(%)	91.64	91.56	93.68
Sensitivity (%)	82.28	83.96	90.66
Specificity (%)	84.86	86.62	87.72
F1-score (%)	84.94	86.08	87.78
Kappa score (%)	69.26	71.04	74.22

5. Conclusion

ADHD is a useful neuropsychological assessment to balance diagnostic assessment. Moreover, it is an objective indication of cognitive malfunctioning of ADHD persons. Generally, cognitive and psychiatric disorders exhibit ocular symptoms which are common in several diseases or even specific to a certain disease. Neuropsychological disorders cause various psychological and economic hindrances and thus precise analysis is required for which deep-learning algorithms can be employed. The objective of this study is to develop a deep learning model using CAAT for predicting ADHD. The proposed Auto Encoder Based Hidden Markov Model (AE-HMM) normalizes the features thereby reducing the batch effects across populations and datasets. This analysis is done by comparing the proposed model with two standard approaches namely CogniLearn and 3-D Convolutional Neural Networks (3D CNN). It is found that the proposed AE-HMM method achieves 93.68% of accuracy, 90.66% of sensitivity, 87.72% of specificity, 87.78% of F1-score and 74.22% of kappa score. The future work concentrates on including behavioural assessment test with fuzzy interference concept for analysing different scores in neural network.

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