Depress-DCNF: A Deep Convolutional Neuro-Fuzzy Model for Detection of Depression Episodes Using IoMT

Akshi Kumar[a], Saurabh Raj Sangwan[b], Anshika Arora[b,*] and Varun G Menon[c]

[a] Department of Computing and Mathematics, Faculty of Science and Engineering, Manchester Metropolitan University Manchester, United Kingdom

[b] Department of Computer Science and Engineering, Netaji Subhas University of Technology, New Delhi, India

[c] Department of Computer Science and Engineering, SCMS School of Engineering and Technology, Kerala, India

[*]Corresponding author: anshika.arora.trf19@nsut.ac.in

Abstract

Discernible patterns of a person's daily activities can be utilized to detect behavioral symptomatology of mental illness at early stages. Wearable Internet of Medical Things (IoMT) devices with sensors that collect motion data and provide objective measures of physical activity can help to better monitor and detect potential episodes related to the mental health conditions at earlier, more treatable stages. This research puts forward a neuro-symbolic model which uses learnable parameters with integrated knowledge for detection of depression episodes using IoMT based actigraphic input. A novel deep fuzzy model, Depress-DCNF is a hybrid of convolutional neural network (CNN) and an adaptive neuro fuzzy inference system (ANFIS) where CNN is used to extract high-level features from the motor activity recordings which are eventually combined with the discriminative statistical features to produce an optimized feature map. This optimized feature map is finally used to train the ANFIS model which accurately performs the depression classification task. The model is validated on the Depresjon benchmark dataset and compares favorably to state-of-the-art approach giving a superior performance accuracy of 85.10%.

Keywords: Convolutional Neural Network, Depression, Fuzzy Inference System, IoMT, Motor activity

[*] Corresponding author.
Email address: anshika.arora.trf19nsut.ac.in

1. Introduction

An individual's personality is a relatively distinct & consistent pattern of thinking, feeling, and behaving. It entails how an individual affects others and how he/she understands and views himself/herself. This general style of interacting with the world which is primarily shaped by life experiences and genetics is often prone to psychological disorders like depression and anxiety. Mental, neurological and substance use disorders make up 13% of the total global burden of disease, leading to shortened life expectancy and dramatic quality of life differences. Depression is a mood disorder that causes distressing symptoms and affects how one feels, thinks, and handles daily activities, such as sleeping, eating, or working. It alone affects 3.8 percent of the world's population, with 5.0 percent of adults suffering from it. It makes an individual cynical and is deeply self-damaging.

Recently, various modeling tools and natural language processing capabilities have been used to analyze the instantaneous behavior, traits, moods and mental disorders such as stress and depression [1, 2]. The Internet of Medical Things (IoMT) is poised to become a transformational force in healthcare. It has emerged as the miracle solution to deal with an overloaded health system offering a myriad of benefits such as remote patient monitoring, improved preventive care, workflow optimization and stock management [3-6]. Certainly, tangible cues from psycholinguistic markers on social media and the IoMT based multimodal signals (audio, video) combined with the sensor-based psychophysiological and brain signals can help to comprehend the affective states, personality traits, emotional experiences and psychological disorders in individuals.

Wearable IoMT devices record user's movements in changing environments and can facilitate crisis intervention for the depressed, distressed and suicidal individuals [7, 8]. The curated flow of information delivered using the wearable technology in a digestible, easy-to-understand format, can deliver interventions for depression [9, 10]. Actigraph sensor is one such widely used wearable sensor that is used to evaluate the physical activity and sleep of an individual [11]. It is a non-invasive method of monitoring the human rest/activity cycles. The motion patterns are displayed as actograms that show the daily activity and rest periods and this data can be analyzed to provide a variety of objective endpoints about the circadian patterns, the level of activity, and the nighttime movements. Eventually, this actigraphic pattern analysis allows depression screening of individuals and serves as a diagnostic parameter for identifying depression episodes.

Artificial intelligence (AI) and natural language processing (NLP) capabilities have reportedly been used to analyze the instantaneous behavior, traits, moods and mental disorders such as depression, schizophrenia, and dementia [1, 2]. Learning algorithms have become more precise and accurate as these interact with training data, allowing humans to gain unprecedented insights into diagnostics, care processes, treatment variability, and patient outcomes. Deep learning models are the state-of-the-art machine learning models that provide an effective way for various medical image & signal analysis as these methods are able to extract high-level features from sequential data discarding the need of manual feature engineering [12-14]. However, stand-alone conventional statistical models, neural networks, and machine learning methods often fail to consider each input's fuzzy uncertainty factors [15]. That is, though the neural models have strong non-linearity and self-learning capabilities, but it has issues like requirement of large training data, high training times, overfitting and parameter tuning. Moreover, for AI to advance, it must understand not only the 'what' but also the 'why'. Deep neural models give black-box predictions and are flawed in their lack of model interpretability which creates trust barriers with human users as cause-effect cannot be explained. In entirety, neural models struggle at capturing compositional and causal structure from data. Alternatively, symbolic models are good at capturing the compositional and causal structure but suffer due to its cumbersome rule-based explicit embedding of human knowledge. A viable unison, a neuro-symbolic system that combines the advantages of both neural networks and symbolic AI techniques is thus the need of the hour. Neuro-symbolic AI uses both logic and language processing to accomplish complex tasks. It primarily incorporates common sense reasoning and domain knowledge into deep learning. Adaptive neuro-fuzzy inference system (ANFIS) is one of the popular combinations that has been extensively used. It can solve the nonlinear "input–output" relationship between models and help eliminate the uncertainty in the feature values of the prediction model. At the same time, these models help in creating networks that are interpretable by design.

Motivated by this, we propose a novel neuro-symbolic model that uses the learning ability of deep neural networks and transparency of the fuzzy system. The proposed Depress-DCNF model combines the capabilities of convolutional neural networks (CNN) and ANFIS for detection of depression episodes from an IoMT based motor activity data. The raw activity measurements are resampled and sequences of 48 hour recordings are used to train the CNN. The high-level features extracted from CNN are then combined with the discriminative statistical features of the activity recordings which are further used to train an ANFIS model. Information gain is used for feature reduction. Thus, the primary contributions of this research are:

- Design a neuro-symbolic classification model for depression detection task based on actigraphic inputs from IoMT for real-time intervention.
- Application of deep learning to achieve generalizability
- Use of ANFIS to better classify the data in extracted feature space than original feature space thereby enabling interpretability under uncertainty
- Evaluation and validation on the benchmark Depressjon dataset for depression screening.

The paper is organized into 5 sections. The following section 2 discusses the related work conducted in the domain. Section 3 discusses the details of the proposed Depress-DCNF model followed by the description of experimental results obtained in section 4 and the conclusion of the research in section 5.

2. Related Work

The prevalence & high risk associated with depression in individuals, early screening efforts and preventive interventions have been studied widely in literature. Recent studies have leveraged the data from wearable devices and soft computing techniques to assess various psychological disorders such as sleep quality [11, 16], depression [17-33], behavioral disorders [16], anxiety [17, 19], and mental wellbeing [20, 21]. Automated detection of depression and its severity assessment using activity monitoring and other multimodal cues is being researched extensively. Moshe et al. [17] attempt to predict symptoms of depression using wearable data. Chiu et al. [22] created a depression dictionary to gather information of depressive users on Instagram. The authors explored image, text and behavior characteristics to detect depressed users on Instagram. In 2021, Zhou et al. [23] studied the relationship between sleep duration and depression in adolescents. Multivariate multilevel logistic regression was applied on the China Family Panel Studies (CFPS) dataset. Colak et al. [24] evaluated the association among sleep quality, depression and anxiety in pregnant women by conducting a cross-sectional study on 149 pregnant patients. O' Callaghan et al. [25] have also associated depression with sleep and performed a literature search to conclude the relationship between depression symptoms and sleep patterns. Other researchers [26-28] have also deduced the relationship between the sleep activity patterns and depression symptoms. Deep learning techniques for prediction of depression have also been utilized in studies. Nguyen et al. [18] propose a deep learning model based on stack generalization and ensemble learning for early diagnosis of depression using wearable data.

Garcia-Ceja et al. [29] propose the Depresjon dataset containing motor activity recording of 23 depressed and 32 non depressed subject and provide a baseline evaluation using SVM. Subsequently, a number of researchers proposed models analyzing the Depresjon dataset. Rodríguez-Ruiz et al. [30] have correlated depression with sleep patterns and analyzed depressive and non-depressive episodes during night time by implementing Random Forest model on Depresjon dataset. In another reported research [31], the authors compared the night and day motor activity to classify the depressive and non-depressive episodes on Depressjon dataset. A number of studies [12, 32, 33] have been reported utilizing the potential of deep learning techniques including CNN and LSTM to automatically extract features from the sequences of the Depresjon dataset.

None of the existing works have combined the high level features extracted from deep learning techniques with the discriminative statistical features of the data. Also, other than baseline machine learning techniques and deep learning techniques, additional soft computing methods have not been explored. Hence, the objective of this study is to use the ANFIS model for classification of depressive and non-depressive states using both the statistical features and the features extracted from CNN.

3. Methodology

The proposed Depress-DCNF model integrates deep learning and ANFIS to implement a deep fuzzy classifier for depression detection using motor activity data. The classifier might prove useful as a first-step to identify depression episodes in the general population, to select patients who might need intervention for confirmed clinical diagnosis and treatment of depressive disorder. The proposed Depress-DCNF model is presented in Fig. 1.

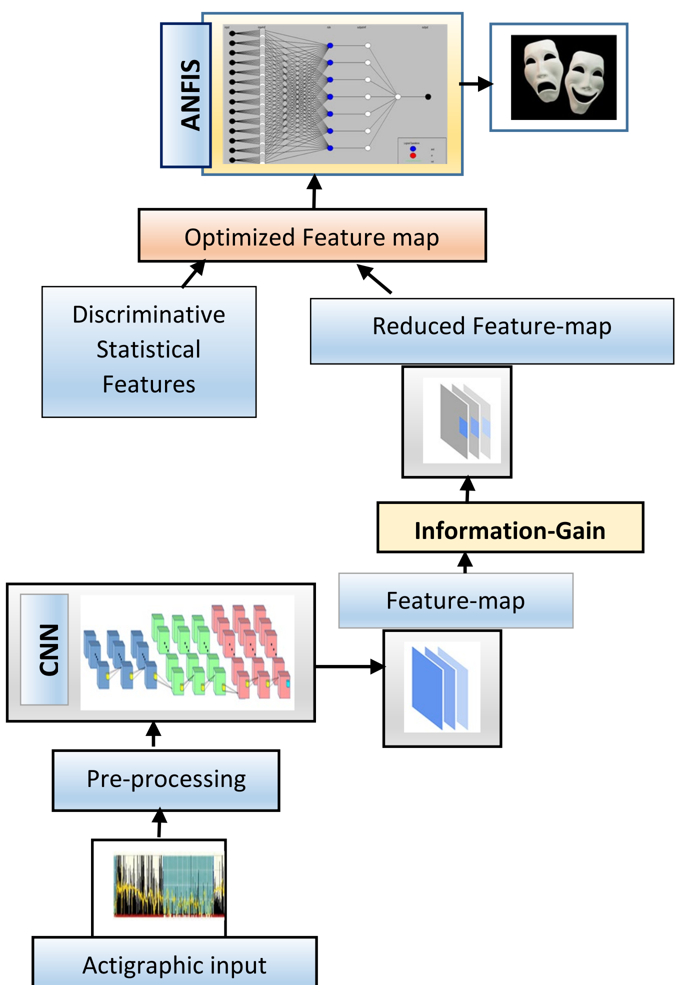

Fig. 1. The Depress-DCNF model

It comprises five key steps namely, data preprocessing (resampling and framing), the convolution neural network for feature extraction, information gain for feature reduction, discriminative statistical feature extraction, and ANFIS model for classification. The benchmark depression dataset, Depresjon is used. The dataset contains motor activity data of 23 depressed (condition) and 32 non-depressed (control) individuals has been used in this study. The condition group consists of unipolar and bipolar depressed patients. The original dataset contains activity count of individuals collected at a sampling rate of 32 Hz using an actigraph device namely Actiwatch, Cambridge Neurotechnology Ltd, England, model AW4. The activity measurements are time stamped at one minute intervals. For each participant, the activity counts of first n days are considered in this study to compare the results with state of the art. Before feeding the data into the proposed architecture, preprocessing including resampling and framing is done. For all the users, the number of days considered in this study is taken as mentioned in the scores file of the original dataset [29].

3.1. Data Preprocessing: Resampling and Framing

The data is down-sampled to 2 hour average intervals. Subsequently, a non-overlapping sequence window of 24 samples is formed corresponding to frames of 48 hours average activity. Therefore, data of 2 days activity has been used for training the model. The data is down-sampled keeping in mind that a person performs an activity for a reasonable duration of time. This size of frames is chosen based on the evidences from previous studies [32] which states that the best performance is achieved with segments of 48 hours activity. This leads to a dataset with 140 instances of the condition group and 195 instances of the control group.

3.2. Convolutional Neural Network

Deep Learning architectures like CNN have the potential to learn high-level features from raw physiological data. This can be used to design models to assess various mental health impairments like depression eliminating the need for domain expertise and hardcore feature extraction [13, 14]. The preprocessed data segments have been fed into the CNN model for extraction of features from activity recordings.

The architecture of CNN used in this study consists of 4 convolution layers where every layer comprises some filters. The role of every filter is to detect a specific feature from the locations of the input sequence. In each convolution layer, the output from ith feature map, given by y_i^l , after the convolution operator is calculated as given in (1).

$$y_i^l = b_i^l + \sum_{j=i}^{m} f_{i,j}^l * y_j^{l-1} \tag{1}$$

where, l is the layer having m filters
$f_{i,j}^l$ is the convolution filter,

y_j^{l-1} is the output obtained from the previous layer, and
b_i^l denotes the bias matrix.

In this work, the first two convolution layers are composed of 64 filters with each kernel size 6. The next two convolution layers are composed of 32 filters each with kernel size 3. Each convolution layer is combined with the ReLU activation function to handle non-linearity. Feature map obtained from the convolution operation is fed into a max pooling layer. Max pooling takes the largest element from the feature map and reduces the dimensionality of the feature map. This helps retain the most significant features. The pool size used in this study is 3. The pooling operation is expressed in (2).

$$pool = \max\{v1, v2, v3, \ldots\ldots v_{d-s+1}\} \tag{2}$$

where, s is the size of the last convolving filter size.

The pooled features are sent to a flatten layer which transforms the feature set into a one dimensional feature vector suitable for classification task. The feature vectors extracted from the flatten layer are used for further steps.

3.3. Feature Reduction

A large feature set may increase complexity of the classification model which potentially leads to high computational time. Hence, Information Gain is used for feature reduction. Information gain attribute evaluator evaluates the worth of an attribute by measuring the information gain with respect to the class where information gain is calculated as given in (3). It determines how each attribute is contributing to decrease the overall entropy where the entropy indicates the degree of impurity [34].

$$\mathrm{InfoGain(Class, Attribute)} = \mathrm{H(Class)} - \mathrm{H(Class|Attribute)} \tag{3}$$

where, H(Class) is the entropy of the class and is given by (4).

$$\mathrm{H(Class)} = -\sum \mathrm{P_i} * \log_2(\mathrm{P_i}) \tag{4}$$

where, P_i is the likelihood of occurrence of the class.

Information Gain is employed on the feature map extracted from the CNN model and a reduced feature map is obtained.

After this step, the feature set size reduced by more than 88%. This optimal set of high-level features is used further for training the ANFIS model which reduces the training time by 72%.

3.4. Discriminative Statistical Features

Discriminative statistical features such as mean and standard deviation of activity measurements along with percentage of events with zero activity over a sequence have the potential to classify depressive and non-depressive groups as proposed by Garcia-Ceja et al. [29]. A feature vector having the three statistical features over a sequence of 48 hours is extracted from the raw data. For extraction of statistical features, a frame size of 2880 is chosen corresponding to the activity of 48 hours. This vector combined with the feature vector extracted from the CNN is fed into the ANFIS model for classification.

3.5. ANFIS

ANFIS model is based on the structure of a multilayer feed-forward network works on the principle of the learning of neural networks combined with the imprecision handling of fuzzy inference systems [16]. Input features are mapped to input membership functions which are mapped to if–then rules. The rules are referred to generate the output structures. Lastly, output features are mapped to output membership functions. An output decision is taken on the basis of the intermediate mappings.

The input feature vectors are fed into the ANFIS model where the first layer consists of adaptive nodes which map the input values to fuzzy membership values as represented by (5).

$$\mu_{Ai}(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}} \tag{5}$$

where, $\mu_{Ai}(x)$ ranges from 0 to 1. Membership functions are tuned using a_i, $b_i$and c_i.

The membership values produced by the first layer are sent to the second layer which is composed of fixed nodes which produces the product of membership functions of the input features as its output. The equation for the same is given below.

$$O2, i = w = \mu Ai(x) \,.\, \mu Bi(x) \tag{6}$$

The output from the second layer is fed into the third layer of the ANFIS model which comprises fixed nodes. At this layer, the ratio of firing strength of ith rule to the sum of firing strength of all rule's is calculated. The normalized firing strength is produced as output. This is in given in (7)

$$O_{2,i} = \frac{\overline{w} \times w_1}{(w_1 + w_{2)}} \tag{7}$$

The next layer comprises adaptive nodes. This layer gives output as presented in (8).

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{8}$$

where, {pi, qi, ri} is the parameter called consequent parameters.

The last layer comprises fixed nodes where all the input signals are combined and an output is generated. This is represented by (9).

$$O_{5,i} = \sum \overline{\mathrm{w_i}}\, \mathrm{f_i} \tag{9}$$

4. Results

This study proposes a deep convolutional neuro fuzzy model for depression detection where the capabilities of convolutional neural network to learn features are combined with the abilities of fuzzy inference system for classification and handling imprecision. The resampling and framing are done using python. Also, CNN is implemented in python using the Keras library. The information gain for feature reduction is implemented in the Waikato Environment for Knowledge Analysis (WEKA). WEKA has also been used for feature visualization. ANFIS is implemented in MATLAB 2013b. This section presents the results of the study.

4.1. Resampling and Framing

The activity recordings are resampled at 2H average intervals. Fig. 2 and Fig. 3 represent the activity counts w.r.t. timestamps before and after resampling of a depressed and a non-depressed participant respectively.

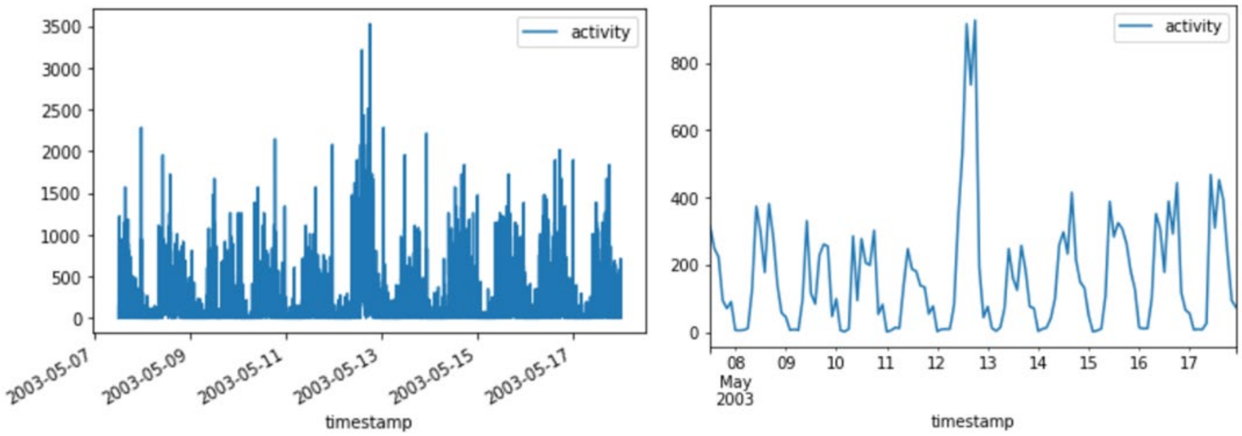

Fig. 2. Activity counts of a depressed patient before and after resampling

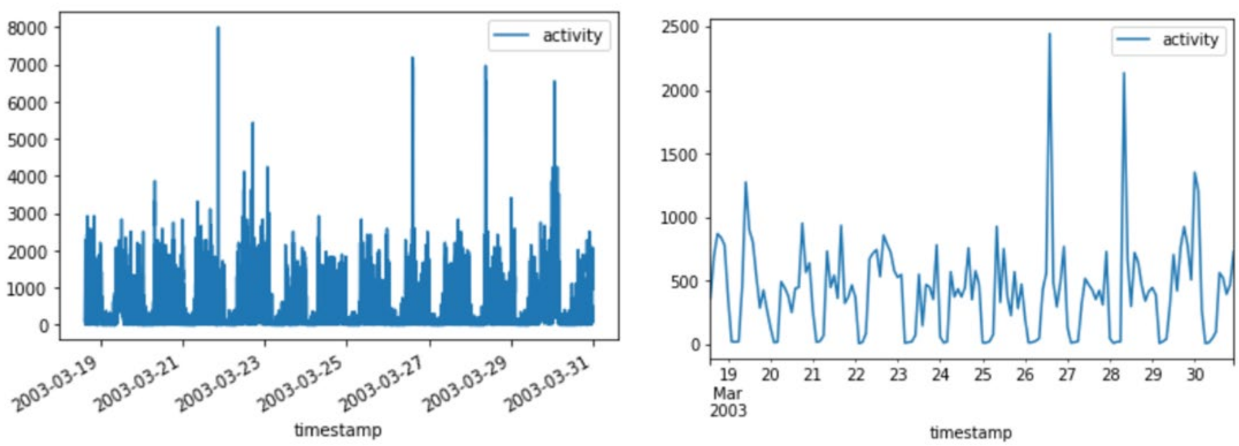

Fig. 3. Activity counts of a control participant before and after resampling

After resampling, sequence window of 24 is used for the formation of segments. When segments of condition and control groups are combined, 335 instances of size 24 X 1 are obtained which are fed as input to CNN.

4.2. Feature Extraction and Reduction

One dimensional CNN model has been used for feature extraction with 4 convolution layers. 64 filters of size 6 are used in the first two convolution layer and 32 filters of size 3 are used in subsequent convolution layers. A max-pooling layer with pool size of 3 has been used after the last convolutional layer. We do not use pooling layers after each convolutional layer to better understand the effects of the convolution operation for feature extraction. Subsequently, a flatten layer, followed by a fully connected layer, a dropout layer, and another fully connected layer, i.e. the output layer has been used. The first fully connected layer comprises of 32 neurons while the output layer consists of 2 neurons corresponding to 2 the classes. ReLU activation function is used at all the hidden layers while Softmax activation function is used at the output layer. Adam optimizer has been used with categorical cross entropy as the loss function. Table 1 gives the summary of the CNN architecture used for feature extraction from sequential activity measurements.

Table 1 CNN Architecture Summary

Layer	Activation function	Output Shape	Parameters
Convolution	ReLU	(, 19, 64)	448
Convolution	ReLU	(, 14, 64)	24640
Convolution	ReLU	(, 12, 32)	6176
Convolution	ReLU	(, 10, 32)	3104
Max Pooling	--	(, 3, 32)	0
Flatten	--	(, 96)	0

The one dimensional feature vector with 96 features is fed into the information gain algorithm with the target to retain only the important features. The features with information gain score below 0.1 have been discarded and a reduced feature map is obtained. Moreover, three discriminative statistical features (mean, standard deviation, percentage of inactivity) are extracted from the raw activity counts which are then combined with the reduced feature map to train the classification model. Fig. 4 shows the distribution of various extracted features w.r.t. condition and control classes.

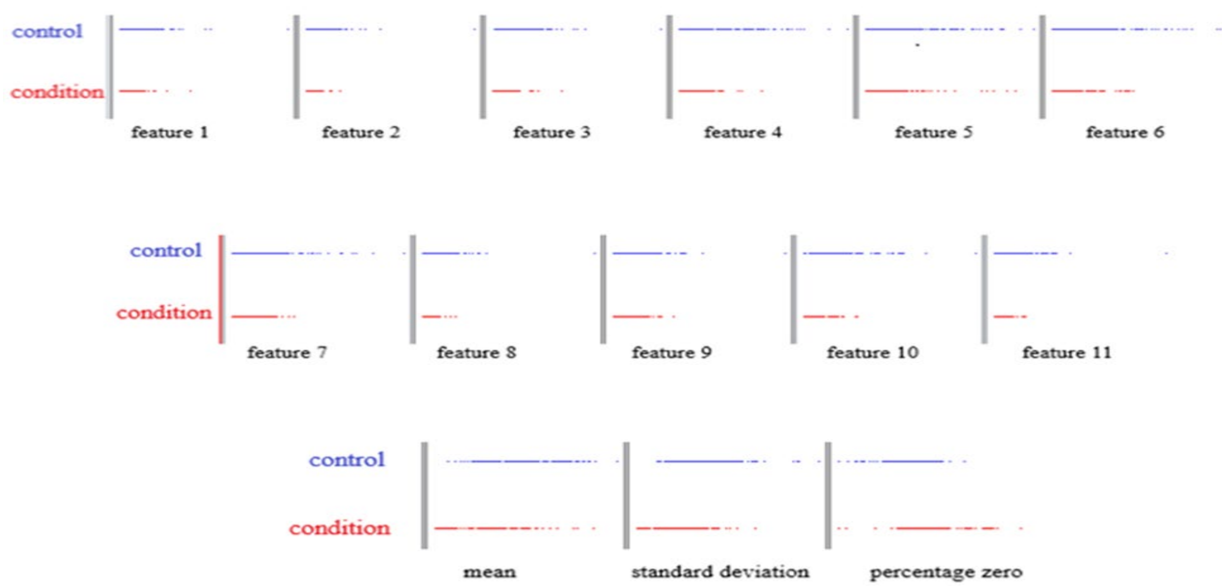

Fig. 4. Distribution of features w.r.t. condition and control classes

4.3. ANFIS

This study uses MATLAB for the implementation of ANIFS. The ANFIS system is trained with the high-level features extracted by CNN with the discriminative statistical features. The dataset is split into a train and validation set in the ratio of 8:2. Table 2 lists the hyper parameters used to generate the FIS. Subtractive clustering method is used for generating the FIS. For training the FIS hybrid optimization method is used which combines gradient descent and least squares model.

Table 2 Hyper Parameter Selection	
FIS type	Subtractive clustering
Opening step size	0.01
Step size increase rate	1.1
Step size decrease rate	0.9
Error tolerance	0
Optimization method	hybrid

A FIS is generated with 14 inputs and 1 output. Fig. 5 represents the FIS generated.

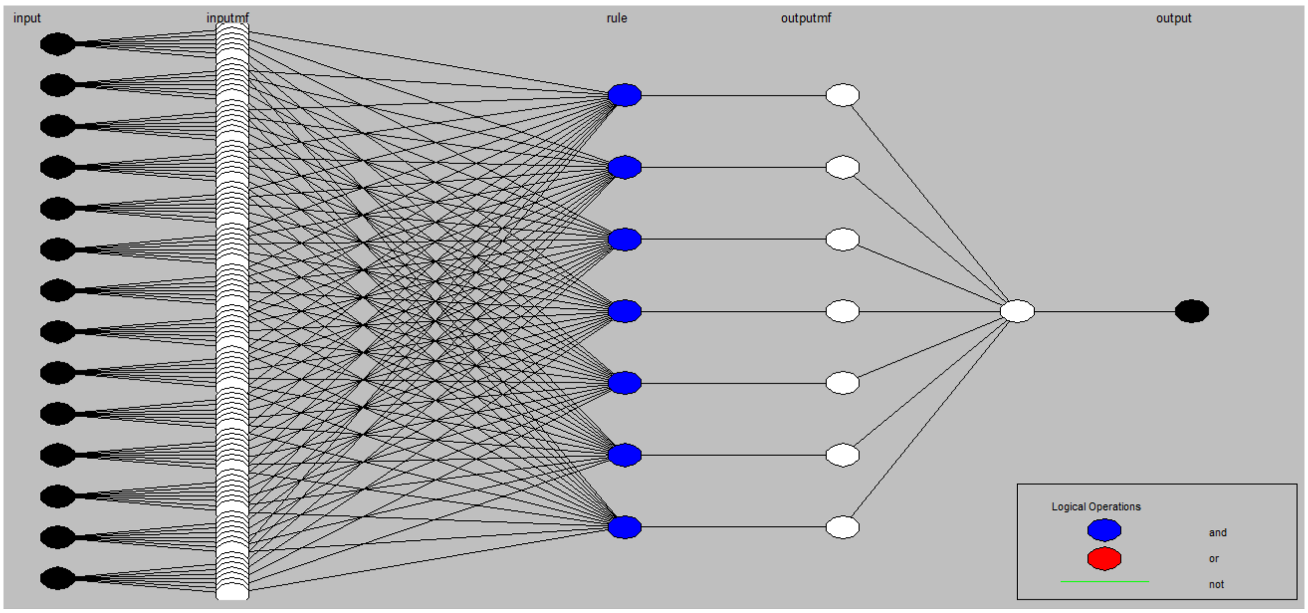

Fig. 5. Structure of generated FIS

Initially the FIS was trained till 200 epochs. Fig. 6 shows the plot of training error against each epoch.

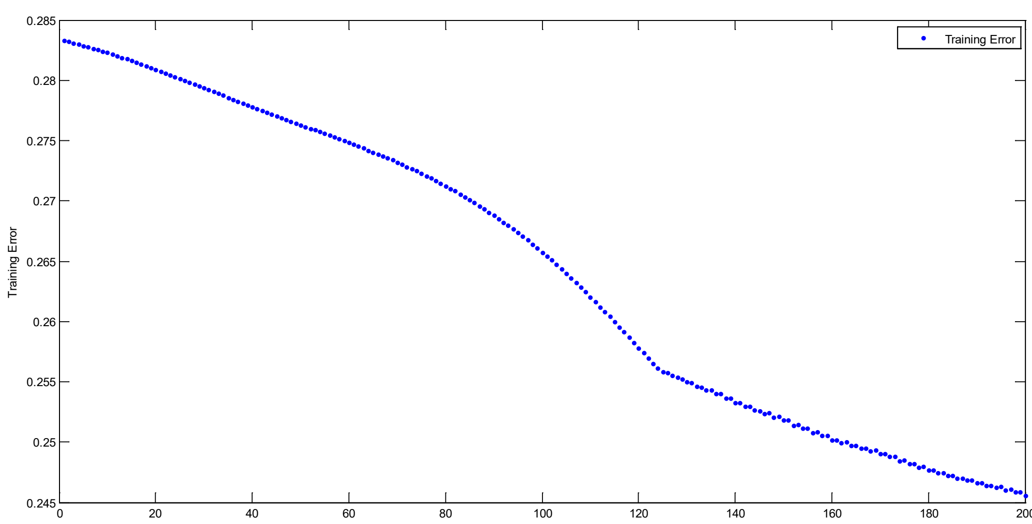

Fig. 6. Training error

Fig. 7 plots the training error and validation error corresponding to each epoch. The validation error decreases till epoch 60 and then increases. Subsequently, the FIS is trained till epoch 60 to retain the best generalization performance.

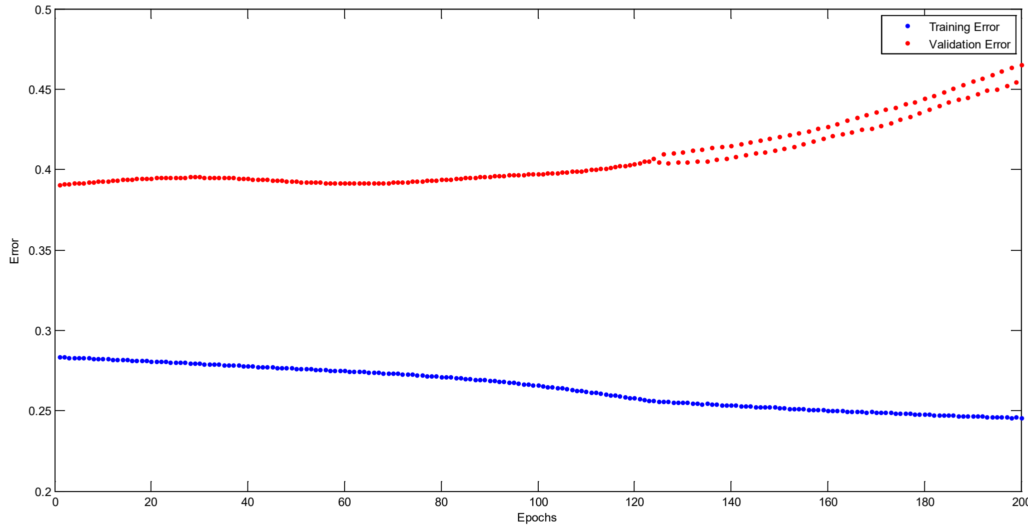

Fig. 7. Training and validation error

Table 3 gives the training and validation errors of the trained FIS.

Table 3 Training and Validation Error

Epoch	Training error	Validation Error
60	0.2644	0.3825

The total number of parameters is 301 for the trained FIS. 7 fuzzy rules are generated. The complete ANFIS information is given in Table 4. Fig. 8 plots the step size with respect to epochs.

Table 4 Summary of trained ANFIS

ANFIS Data	Value
Number of nodes	227
Number of parameters	301
Number of fuzzy rules	7

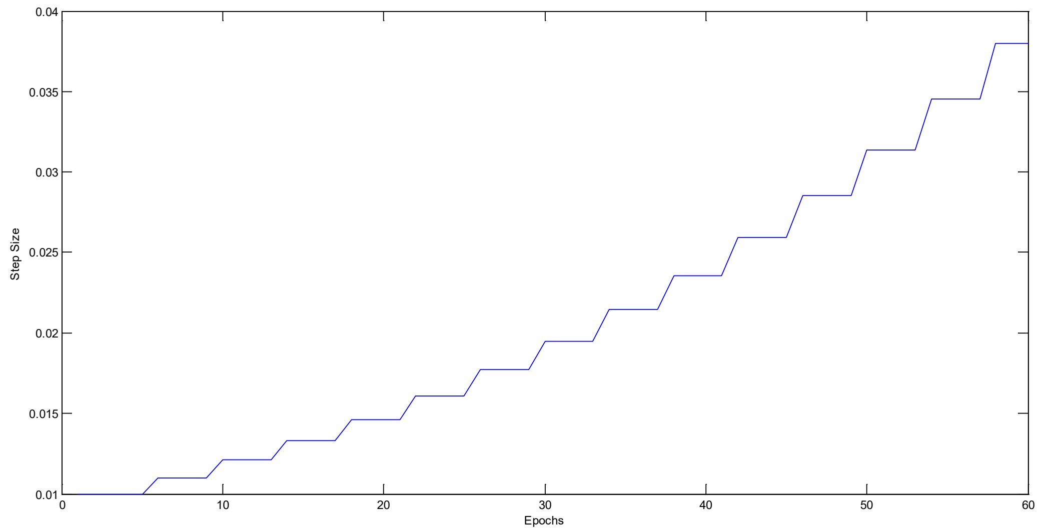

Fig. 8. Step size

Table 5 presents the performance of the trained ANFIS model in the form of average testing error.

Table 5 Trained ANFIS Information

Dataset	Average Testing Error
Training data	0.2778
Validation data	0.3934

The performance of the proposed framework is also evaluated using mean absolute error (MAE) and accuracy. The proposed model gives MAE of 0.241 and accuracy of 85.10%.

4.4. Comparison with CNN and LSTM

The performance of the proposed framework has been compared with other deep learning models including CNN and LSTM. Resampling and sequencing is done in a similar way. However, discriminative statistical features are not included to train the CNN and LSTM models. The comparative results are presented in Fig. 9.

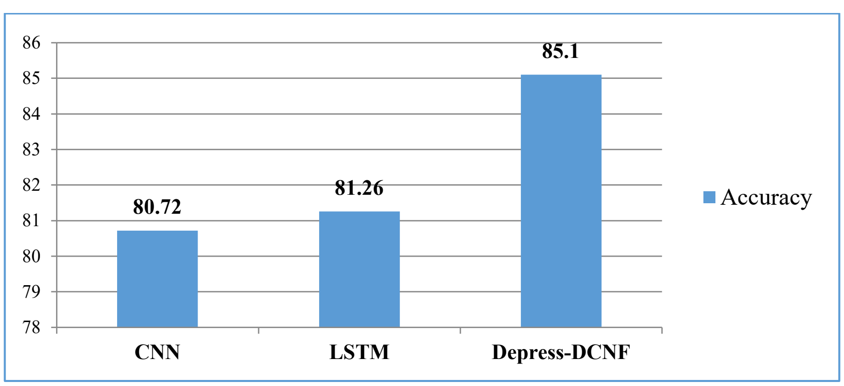

Fig. 9. Performance comparison with CNN and LSTM

It can be observed that the proposed convolutional neuro fuzzy framework for classification between control and condition groups outperforms other deep learning models achieving an accuracy of 84.10%. CNN is capable of evaluating features and learning temporal structure in subsequences in which localized patterns are captured by filter because the filter works at a subset of the sequence. CNN performs almost as good as the LSTM with less computational effort and less training time due to localized connections [12]. The performance improves significantly on implementing neuro-fuzzy inference system on the top of CNN as it provides a classification model handling imprecision and uncertainty in the time-series sequences which cannot be handled by CNN unaided. The accuracy improves by approximately 4% on utilizing the neuro-fuzzy system.

4.5. Comparison with State of the Art

The performance of the proposed framework is compared with state of the art results involving "The Depression Dataset". Table 6 presents the comparative results.

Table 6 Comparative Performance with Existing Models

Study	Technique	Features	Accuracy
Garcia-Ceja et al. [29]	SVM	Statistical	72.7
Sharanan Kulam [12]	LSTM	High-level	82.00
Sharanan Kulam [12]	CNN	High-level	82.00
Frogner et a. [32]	CNN	High-level	71.00
Jakobsen et al. [33]	DNN+SMOTE	High-level	84.00
Proposed framework	**Convolutional neuro fuzzy**	**High-level + statistical**	**85.10**

It can be observed that the proposed model outperforms the state-of-the-art results using the motor activity data for depression prediction.

5. Conclusion

This study proposed a hybrid deep fuzzy model for depression classification using motor activity recordings of 23 unipolar & bipolar depression patients with 32 controls in the "The Depression Dataset: Depresjon". The novel Depress-DCNF combines the capabilities of convolutional neural network to learn high-level features with that of fuzzy logic for improved classification and handling imprecision. The initial layers of CNN are used to extract the high-level features from 48 hour sequences of motor activity recordings which are combined with the discriminative statistical features. Information gain is used for reduction of the size of feature map in order to retain relevant features. The combined feature map is then used to train an ANFIS model to classify the user states as depressive and non-depressive. The model enables accurate and interpretable predictions. It is observed that the proposed neuro-symbolic model outperforms other deep learning models and gives superlative performance accuracy of 85.10% when compared to the state-of-the-art models.

The limitation of the proposed methodology is that it does not take into account non-depressive reasons of low activity such as injury, sickness, old age etc. In future more technically advanced models can be built based on motor activity counts combined with subject's social media posts so as to accurately predict depression as social media analysis have been successfully studied independently to predict depression in users [35, 36].

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