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An Efficient Methodology For EEG-Based Emotion Detection Using Feature Optimization And Ensemble Classifier

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Abstract

Emotion is a fundamental way to represent the behaviors and activities of humans. However, the accuracy of automatic emotion detection is a challenging task for the machine. The detection of emotion decides the activity states of action. Electroencephalogram (EEG) signals play a vital role in detecting human emotion in the mode of arousal and valence. However, the dimension and complexity of electroencephalogram signals decline the performance of the classification algorithm. This paper proposed an ensemble-based classification algorithm for the detection of human emotion. The ensemble-based classifier uses three different classifiers conventional neural network (CNN), support vector machine (SVM) and decision tree (DT). The process of ensemble follows the rule of boosting. The major challenge for the classification of EEG signals is the decomposition of signals and the selection of features of EEG. The extraction of EEG features applies wavelet discrete transform methods and uses a glowworm optimization algorithm to reduce the lower content of features as artefacts and noise. The optimized features of EEG signals reduce the vector divergence factors of the ensemble classifier. The proposed ensemble classifier is tested on Deepa datasets and measures standard parameters such as precision-recall and F-measure. The analysis of the results suggests that the proposed algorithm is more efficient than CNN and DL machine learning algorithms.

Keywords: - EEG, CNN, SVM, DT, Emotion Detection, Ensemble Classification

Introduction

The brain-computer interface (BCI) plays a vital role in mapping unstable activity of the human brain. The BCI integrates electronic devices with the human brain in the form of computers and mobile devices. The role of BCI is very efficient in detecting critical illnesses related to the human brain [1,2,3]. The BCI recoded the Electroencephalogram signals, and these signals are a collection of brain activity between different windows frame [4]. The Electroencephalogram signals are very complex and have high dimensions, so analysis of signals faces classification challenges. Nowadays, emotion detection is the new area of research based on Electroencephalogram signals. Emotion has defined the nature of humans in the form of activity and behaviors. The emotion of humans is the collective composition of valance, aerosol and dominance. Emotional arousal detection plays a vital role in diagnosing psychological disorders such as anxiety in humans [5,6,7]. Most authors focus on emotion-focused therapy (EFT) for the successful analysis of disorder of psychological disorders. However, detecting arousal emotion is very difficult to the human-computer interface. The brain-computer interface collects brain information with various electrodes connecting the surface of the human brain. The collection of EEG signals in the form of analog and further converted into digital form for the processing of classification algorithm [8,9,10]. The classification of EEG signals proceeds in three phases: pre-processing, feature extraction, and classification. In the pre-processing phase, applying a low pass filter removes the local collection of noise and improves the quality of signals. In the feature extraction phase, extract the lower content of features of EEG signals [11,12,13,14]. The lower content of features is estimated as variance, mean and entropy of signals bands of raw EEG signals. Finally, the classification algorithms categories the EEG signals band and predict the actual bands of signals of individual moments of emotion as arousal, valance and dominance. The incremental approach of emotion detection based on EEG signals focuses on feature extraction and classification algorithms. The feature extraction of EEG signals faces significant challenges due to the complex structure of signals and the high data dimension. EEG signals' most dominant feature extraction methods are discrete wavelet transform and its derivates, such as wavelet packet transform and hybrid transform. The discrete wavelet transform decomposes EEG signals in lower features content in terms of entropy, mean and variance of energy factors. The diverse space of feature components faces the problem of feature selection and mapping features for the classification algorithm [15,16,17,18]. The mapping and selection of features in classification use swarm intelligence-based algorithms. The swarm intelligence algorithms scale the efficiency of the feature selection approach in EEG signals classification. This paper applies a glowworm swarm optimization algorithm to select EEG signals for emotion detection. To classify the emotion, EEG recorded signals face more challenges than extracting EEG signals' features. Recently various authors applied machine learning algorithms such as Convolutional neural networks (CNN) and deep learning algorithms. The CNN and deep learning algorithms enhance the classification of emotion detection. This paper proposed an ensemble-based classification algorithm for the detection of emotion [19.20,21]. The principle of ensemble classifier applies the CNN network as a base classifier and adds two more classification algorithms, a support vector machine and a decision tree. The support vector machine enriches the feature components of EEG sampled signals. The Decision Tree algorithm selects the high entropy features to boost the processing of the classification algorithm. The evaluation of emotion detection categories as subjective and objective approaches. The subjective approach can be a self-reporting process and prepare the questioner and visual tools. The objective approach uses physiological signals such as blood pressure, heart response, brain activity, etc [22,23,24]. This paper evaluates the algorithm using the DEPA datasets. The main objective of this paper is to enhance emotion detection using the proposed algorithm. The second objective of this paper is to compare existing algorithms with the proposed algorithm. The Rest of the paper is organised as in section II. Related work, in section III. Proposed methodology for emotion detection. In section IV, experimental analysis of the proposed algorithm; in section V, conclusion and future work of the proposed algorithm.

II. Related Work

EEG-based emotion detection is a new area of research in intelligent systems. The behaviours of humans represent the impact of emotion in different ways, such as anger, happiness, sadness, normal and negative or positive. The role of EEG signals decodes the physiological perception of human activity. The contribution of authors enhances the classification and recognition ratio of emotion. Recently contribution of algorithms is described here. In this [1] author proposed the DEAP benchmark database to construct a subject-independent emotion identification system. To categories low–high valence and similarly low–high arousal, a deep neural network with a simple design is utilized in this study. Signals from the electroencephalogram (EEG) are nonstationary. In this [2] author propose A discrete Wavelet Transform-based approach is used to recognize emotions from EEG signals. Wavelet Energy and Wavelet Entropy, two of the most important properties, are estimated to detect four different emotions: joyful, furious, sad, and relaxed. On the internationally recognized 'DEAP' database, their proposed technique had 78.72.6 percent sensitivity, 82.86.3 percent specificity, and 62.31.1 percent accuracy. In this [3] author propose EEG signals will be used to determine emotional states using the AMGLVQ approach. The DEAP dataset contains uneven data, and one of the advantages of the AMGLVQ approach is that it can manage classification in such cases. The tests show that AMGLVQ outperforms RF and SVM. In this [4] author using typical feature selection approaches, Deep Feature Clustering (DFC) is used to aggregate the properties of many neural networks to choose high-quality qualities. The recommended strategy enhances emotion identification performance in a short processing time and is more competitive than the newest emotion recognition methods, based on the categorization efficiency of the SEED, DEAP, and MAHNOB collections combined with the possibilities of DFC. In this [5] author Using sequence classification, discover the talented RNN variation network LSTM with long-term memory by combining EEG signals, emotion detection, and RNN cyclic neural networks. It will increase the accuracy of emotional monitoring depend on EEG signals, allowing for more realistic monitoring of learners' emotional enthusiasm. In this [6] author present an automated methodology for detecting emotions using EEG waves. The suggested model aims to develop a method that effectively combines the essential steps of EEG data processing and feature extraction. Experiments confirmed the efficacy of the proposed strategy, with the CNN-based method achieving a 95.20 percent accuracy. In this [7] author propose An audio-video stimulus-based experimental setup and a two-stage emotion filtering method are used to create electroencephalogram (EEG) recordings of joyful, fear, sad, and relax emotions. The detection of EEG signals is available. Using the MW kernel function, individual classification accuracies for joyful, fear, sad, and calm emotions are 92.79 percent, 87.62 percent, 88.98 percent, and 93.13 percent, respectively. In this [8] author propose that multi-channel features be learned from the EEG signal, which is generated by sound signal stimulation, for human emotion identification. Experiments on the DEAP dataset show that their proposed strategy enhances recognition accuracy rate when compared to frequency domain feature-based emotion recognition algorithms. In this [9] author propose a deep learning framework for detecting emotions from electroencephalograms (EEG). T Section is made up of temporal and spatial convolutional layers that simultaneously develop discriminative representations in time and channel domains. SVM, EEG Net, and LSTM are all used to compare the suggested technique. T Section has a high classification accuracy of 86.03 percent, greatly outperforming the previous techniques (p0.05). In this [10] author Deep CNN models, as well as shallow machine learning models like BT, SVM, LDA, and BLDA, were utilized to perform emotional binary classification studies on DEAP datasets in the valence and arousal dimensions. According to the testing results, deep CNN models without feature engineering performed 3.89 percent better in valence and 3.06 percent better in arousal than the best standard BT classifier. In this [11] author provide an integrated system for semi-generic emotion identification that combines independent component analysis for EEG pre-processing, unsupervised learning for EEG subject grouping, and an EEG-based emotion recognition CNN When compared to the reported accuracies of the generic emotion classifiers, the suggested transfer learning technique enhances the CNN classifier's valence and arousal accuracy to 70.26 percent and 72.42 percent, respectively. in this [12] author propose EEG signal pre-processing, suggest a maximum marginal technique. The method uses the least similar regions of two EEG signals as features to indicate the difference in EEG signals caused by emotions. The experimental output demonstrate that the suggested methodology outperforms other feature selection approaches in terms of accuracy by 17.9% on average. In this [13] author Using VMD as a feature extraction technique and a Deep Neural Network as the classifier, a subject independent emotion recognition technique is presented from EEG data. The suggested method outperforms state-of-the-art algorithms in subject-independent emotion identification from EEG when tested with the benchmark DEAP dataset. In this [14] author developed a method for extracting and selecting spatial features with a minimal processing time. Using the empirical model-based decomposition presented in their work, known as intense multivariate empirical mode decomposition, the raw EEG signal is first split into a smaller collection of eigenmode functions called (IMF). In this [15] author developing a new interpretable emotion recognition approach with activation mechanism has been created using machine learning and EEG inputs. The data support the hypothesis that emotions are triggered gradually throughout the experiment, and that adding weighting coefficients depend on correlation and entropy coefficients can improve EEG-based emotion identification accuracy dramatically. In this [16] author provides a unique approach for emotion recognition depend on time-frequency analysis of multichannel electroencephalography (EEG) signals utilizing the multivariate synchro squeezing transform (MSST). MSST and its univariate counterpart, which used linear support vector machines (SVM) as a classifier, had the greatest prediction accuracy rates of 93 percent among all emotional states. In this [17] author propose Using multivariate EMD, an emotion recognition model is given via EEG signal decomposition. The multivariate EMD technique extracts quasi orthogonal intrinsic mode functions. As a result, the extracted IMFs are orthogonalized using the Gram-Schmidt approach. In this [18] author Utilizing CNN for emotion detection using facial landmarks, they were able to attain a maximum recognition rate of 99.81 percent. However, for emotion identification using EEG signals, the maximum recognition rate attained using the LSTM classifier is 87.25 percent. In this [19] author Using VMD as a feature extraction technique and a Deep Neural Network as the classifier, a subject independent emotion recognition technique is presented from EEG data. The suggested technique outperforms state-of-the-art algorithms in subject-independent emotion identification from EEG when evaluated against the DEAP dataset. In this [20] author propose Singular Spectrum Empirical Mode Decomposition (SSEMD), a new effective method for successful classification of Normal and Epileptic EEG Signals, is proposed. The EEG signal is classified into normal and epileptic classes using high-performance machine learning classifiers. The proposed feature extraction approach has a detection accuracy of 99.8% and practically nil false positive rates. The application of ANOVA output in an average dimensionality reduction of 70% of total feature space. In this [21] author propose a model for recognizing three emotions from physiological signals: amusement, melancholy, and neutral, with the goal of establishing a viable methodology for emotion recognition utilizing wearable devices. The findings suggest that solely galvanic skin response properties may be used to determine amusement, melancholy, and neutral emotions. When tested on the test data set, the system was able to distinguish the three target emotions with up to 100% accuracy. In this [22] author proposes EEG signal emotion identification utilizing a feature extractor and Bi LSTM network classifier depend on LF-DfE. On the DEAP database, the average accuracy of subject noncontingent experiments has improved by 7.04 percent. The suggested feature extractor LF-DfE with the Bi LSTM network was found to outperform existing approaches in experiments. In this [23] author use electroencephalography (EEG) data to assess emotional state and to see if meditation music therapy can help to regulate mental state. The use of music therapy output in a 75 percent beneficial change in the participants' mental state. This work proposes a novel method for analyzing brain EEG waves in detail to detect emotions and stable mental states. In this [24] author aids in the application of spatial PCA to minimize signal dimensionality and the selection of acceptable features depend on t-statistical inferences between classes. The maximum classification accuracy was attained by ANN and SVM in the case of a subject-dependent method. In the case of a subject-independent approach, the proposed method achieves 84.3 percent and 77.1 percent classification accuracy using ANN and SVM, respectively. In this [25] author use two ideas to EEG signal analysis, especially in the areas of brain–computer interface, neurological illnesses, and cognitive analysis they also develop a technique for recognizing tired driving that combines recurrence graphs with a convolutional neural network. The findings reveal that in the instance of EEG signal processing, functional complementarity may be successfully used by complex networks and deep learning to improve feature extraction and classification. In this [26] author propose The effectiveness of emotion recognition using brain signals can be increased by utilizing a novel and adaptive channel selection technique that recognizes that brain activity has a unique characteristic that varies from person to person and emotional state to emotional state. The overall accuracy rate was over 89 percent. The new technique boosted accuracy by 8% when compared to current algorithms that dealt with nine emotions. In this [27] author propose an ensemble learning method is used to automatically compute the most discriminative subset of EEG channels. their technique can help you reduce the amount of data you have while also enhancing computational efficiency and classification accuracy. Experiments on a publicly available EEG dataset show that the suggested algorithm outperforms the alternatives. In this [28] author presents a highly accurate classifier for emotion/quadrant detection from EEG signals. EMD which decomposes the signals into numerous oscillatory IMF, was chosen as the data pre-processing approach. The Multilayer Perceptron classification output surpassed SVM, with a maximum accuracy of 100 percent in the binary classification of High and Low Arousal space. In this [29] author utilizing a spiking neural network to develop an emotion detection system from a reduced version of the DEAP dataset without employing feature extraction methods and keeping reasonable accuracy was studied. The output showed that utilizing a Neu Cube-based spiking neural network, they were able to determine the valence emotion level with 84.62 percent accuracy using only 60 EEG samples, which is equivalent to prior studies. In this [30] author present a comprehensive review of recent literature on state-of-the-art emotion recognition systems, and a description of some of the most common emotion recognition processes, including related definitions, theories, and analyses, to provide critical knowledge for the development of a comprehensive framework Deep learning-based emotion identification systems and shallow machine learning-based emotion recognition systems were also separated from the experiments.

III. Proposed Methodology

The proposed methodology of emotion detection describes in three sections. In first section describes the feature extraction of EEG signals, in second section describes the feature optimization of EEG signals, and in section III. Describes the CNN based ensemble classifier for the classification of emotion detection.

1st section

Feature extraction

The process of feature extraction in EEG-based Emotion Detection is the primary phase. The EEG signals encapsulates the information of human nervous system in different windows time frame. The collected signals of EEG is mixed into different bands such as alpha, beta, gamma, delta and many more sub-component of features. The separation of bands required the process of feature extraction. This paper applies the discrete wavelet transform for the extraction of features. Discrete wavelet transform is rich texture dominated transform method and the processing of transform in terms of high frequency (HF) and low frequency (LF). The part of high frequency data is preserved and further explore low frequency. The processing of discrete wavelet transform describes as the high pass filter [f(n)] is mother of discrete wavelet and low pass filter [h(n)] the mirror type of function [12,13,14]. The process of scaling function db4 shown in figure 2. The proceed product of high pass filter and low pass filter is called approximate and detailed coefficients. The process of scaling [$\varphi_j, k(n)$] and wavelet function [$\psi j, k(n)$] both depends on high pass filter and low pass filter. The represents of this as

$$\varphi j, k(n) = 2^{-\frac{j}{2}} h\left(2^{-j} n - k\right) \dots\dots\dots\dots\dots (1)$$

$$\psi j, k(n) = 2^{-\frac{j}{2}} f\left(2^{-j} n - k\right) \dots\dots\dots\dots\dots (2)$$

The process of derivation define as n=0,1, 2,…….,M-1; j=0,1,2,……,j-1; k=0,1,2,….,2j-1;J=5. The M is length of signal.

The two-coefficient approximate and details measure as (Ai) and Di

$$\mathrm{Ai} = \frac{1}{\sqrt{M}} \sum_n X(n).\, \phi j, k(n) \ldots \ldots \ldots \ldots \ldots .(3)$$

$$\mathrm{Di} = \frac{1}{\sqrt{M}} \sum_n X(n).\, \psi j.\, k(n) \ldots \ldots \ldots \ldots \ldots \ldots .(4)$$

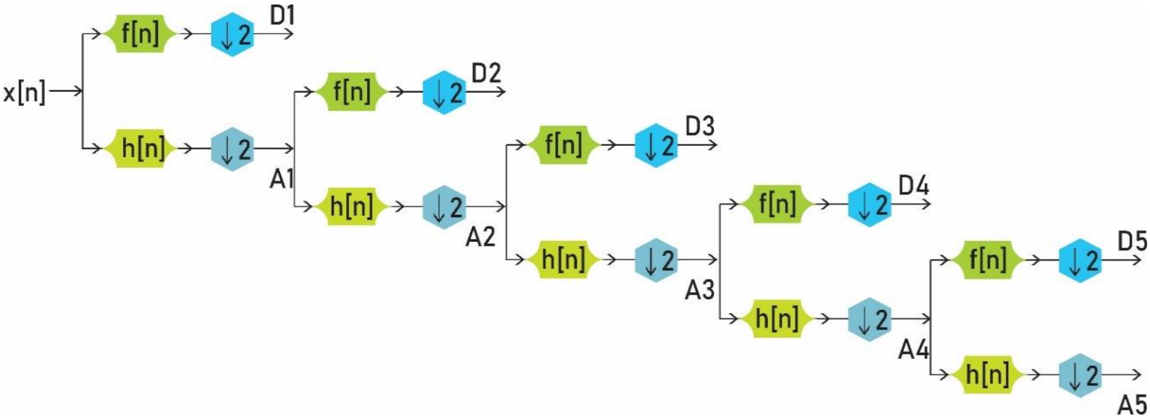

Figure 1 process of EEG signals data decomposition in terms of approximate and details as HF and LF

The processing of wavelet transform generates two features of matrix one is approximate feature matrix and details feature matrix. The extracted features FA={f1,f,2,f3,……………,fn} and other side the features of details as mention as FD={fd1,fd2,fd3,……………….fdn}, the collection of features represents as

FA=$\sum_{j=1}^{n} |Aij| \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .(5)$

FD= $\sum_{j=1}^{n} |Dij|$……………………………….(6)

The total estimated features of transform method is summarizes as

FSA=$\sum_{i=1}^{l} (FA + FD) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (7)$

2nd section

Feature optimization.

Scaling of features of EEG signals applied the approach of feature optimization. The process of feature optimization reduces the lower content of feature of transform methods and enhance the feature selection possibility for the applied classification algorithm. The process of feature optimization applies glowworm optimization algorithm. The glow-worm algorithm based on the concept of local information sharing between glow-worm. The processing of glow-worm is iterative and memory-based process. Initially all the extracted features mapped in feature space of glow-worm as population. The processing of optimization describes as

1. The feature of transform set mapped as i with objective function J(xi(t)) the position of feature data is xi(t) into acceleration α. The value of luciferin li spread with neighbour (Ni(t)) of glow-worm. Each iteration of feature set the new factor of decision is updated by equation (8)

$$r_d^i(t+1) = \min\left\{rs, \max\left\{0, r_d^i(t) + \beta(nt - |Ni(t)|)\right\}\right\} \ldots\ldots\ldots\ldots (8)$$

After the iteration of feature of new neighbours is

$$N_{i(t)=\left\{j:\|xi(t)-xi(t)\|<r_d^i;li(t)<li(t)\right\}} \ldots\ldots\ldots\ldots (9)$$

The movement of feature component by local decision is.

$$p_{ij(t)=\frac{l_{i(t)-l_{i(t)}}}{\sum_{k\in Ni(t)} lk(t)-li(t)}} \ldots\ldots\ldots\ldots (10)$$

Update the new set of features

$$x_{i(t+1)=xi(t)+s\left(\frac{sj(t)-xi(t)}{\|xj(t)-xi(t)\|}\right)} \ldots\ldots\ldots\ldots (11)$$

Update the value if luciferin

$$l_{i(t)=(1-\rho)li(t-1)+\gamma j(xi(t))} \ldots\ldots\ldots\ldots (12)$$

The termination of optimization process gives the set of optimal features of EEG signals and finally convert these features into matrix. The processing of matrix converted into vector of network and proceed into ensemble classifier for the detection of emotion.

Section III

Ensemble classifier

The design ensemble classifier increases the detection ratio of EEG based emotion detection. The main base classifier of ensemble classifier is CNN (convolutional neural network). And other two classifier are support vector machine and decision tree. The CNN model is sub group of deep learning-based classification algorithm, the processing of CNN classification algorithm is feedforwarded neural network. The support vector machine is binary classification algorithm. The processing of support vector machine is maximisers of feature sampling and enhance the voting process of ensemble classification algorithm. The decision tree applies the process of entropy and increase the probability of feature selection and increase the classification process of CNN base classifier and overall, the ensemble classifier enhance the classification ratio of emotion detection. The process of ensemble classifier describes here[24,25,26].

The ensemble of CNN, SVM and DT follow the define constraints function for the process of boosting of classifier. The final output of ensemble classifier by combined the majority voting process of all classifier. The applied CNN classifier maximize the probability of Pn=(Yn1, Yn2,,,,,,,,,,,,,Ynn). The prediction of probability as input of support vectors. As SV=Yn1+Yn2+Ynn. The processing of support vector features mapped to decision tree.

1. Input the N feature set of CNN model, the output of CNN probability input of support vector
2. If min(Yn1, Yn2,…………Ynn) >s is aerosol
3. Else if max(Yn1,Yn2,…….Ynn)< s is valance
4. Where s is factor of separation of valance and aerosol.
5. End

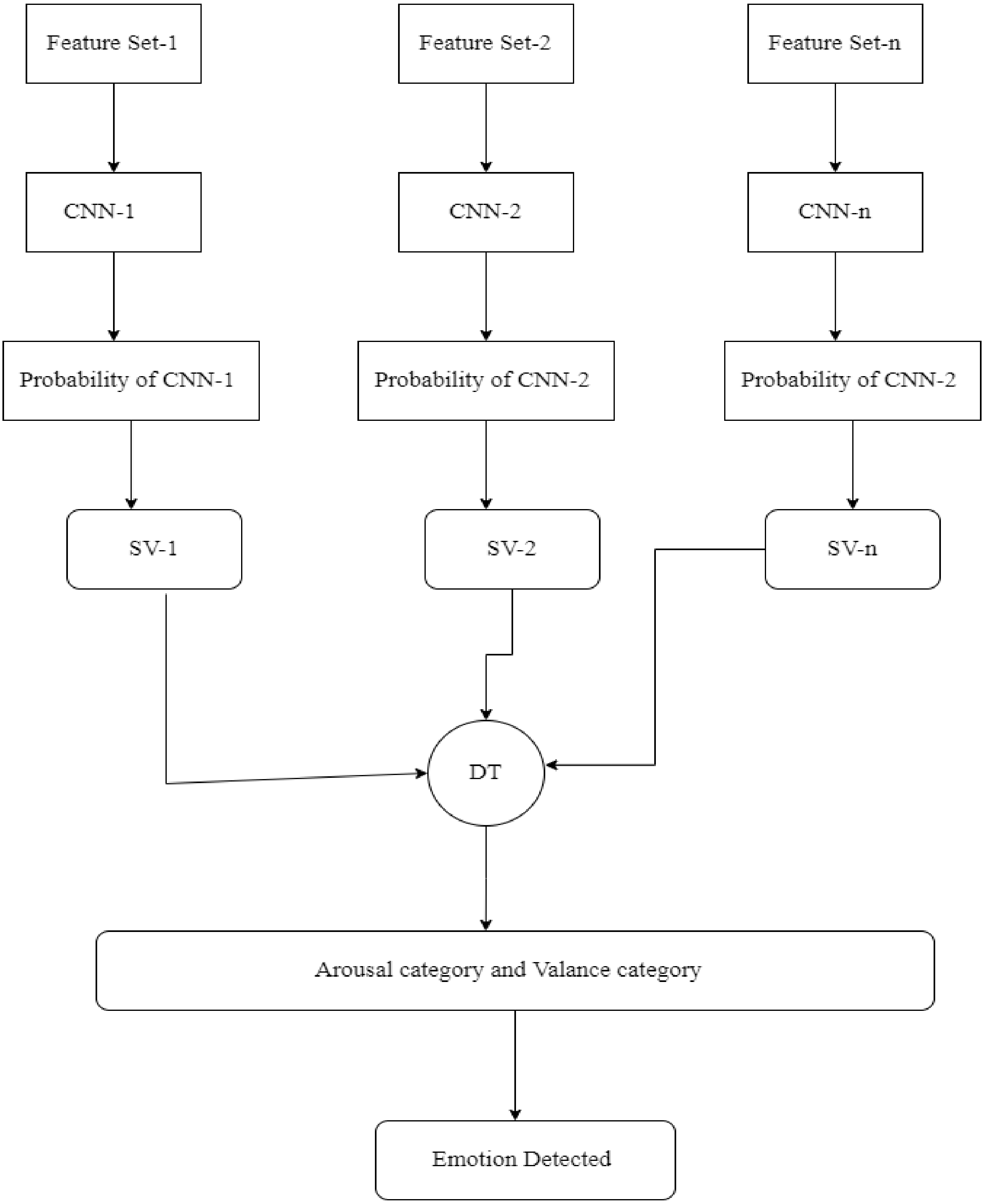

Figure 2 proposed ensemble classification model based on CNN, SVM and DT

Algorithm of ensemble classifier

K -CNN layer

M= SVM machine

N= entropy of DT

X is sample of EEG signal transformed by wavelet

Vx= input vector of ensemble classifier

Vout= voting of classifier

Consider A training sample pairs of Xi and the size of sample data is O and the length of features matrix mapped in training is L. now the processing of ensemble classifier as

$\mathrm{Vx} \leftarrow \mathrm{Xi}$ if $* = \mathrm{K}$ or if $* = \mathrm{X}$

$\left[\mathrm{f}^{1}, \ldots\ldots \mathrm{f}^{\mathrm{k}}\right] \leftarrow [\mathrm{rand}(1, \mathrm{X}) \times (\mathrm{Vx} - \mathrm{l})] + 1$

$\mathrm{Vout} \leftarrow \mathrm{Vx}$ mapping of EEG class

For $\mathrm{i} \leftarrow 1$ to O do

$\mathrm{M} \in \mathrm{K} \leftarrow \mathrm{N}$ if $* = \mathrm{CNN}$ if $* = \mathrm{X}$

$\mathrm{K} \in \mathrm{R}^{\mathrm{m}\,\mathrm{Xn}} \leftarrow$ class of classifer

$\mathrm{Sv} \in \mathrm{R}^{\mathrm{PCNN}} \leftarrow$ vector from of P

End for

Encapsulates features of EEG sample data

$\mathrm{P}_{\mathrm{SV}} \in \mathrm{R}^{\mathrm{d}(=\mathrm{kXn})\times \mathrm{m}} \leftarrow \emptyset([\mathrm{DT}_{*}^{1}, \ldots\ldots\ldots \mathrm{DT}_{*}^{\mathrm{m}}])$

Detection $\in \leftarrow$ Vout (M)

IV. Experimental Analysis

To validate the proposed ensemble classifier for emotion detection uses MATLAB software for the process of simulation. The version of software is R2014a, and the configuration of system is I7 processor, 16GB RAM and windows10 operating system. The MATLAB provides the basic support library file of support vector machine and other classification algorithm. But the other function of classifier defines and programmed with function file and compile with library file. For the process of detection applied DEPA dataset. The DEPA dataset free available for the purpose of study and research. The process of sample of data applied 10 cross folds for the processing of prediction and measurement of parameters such as precision, recall and F-measure [28,29,30].

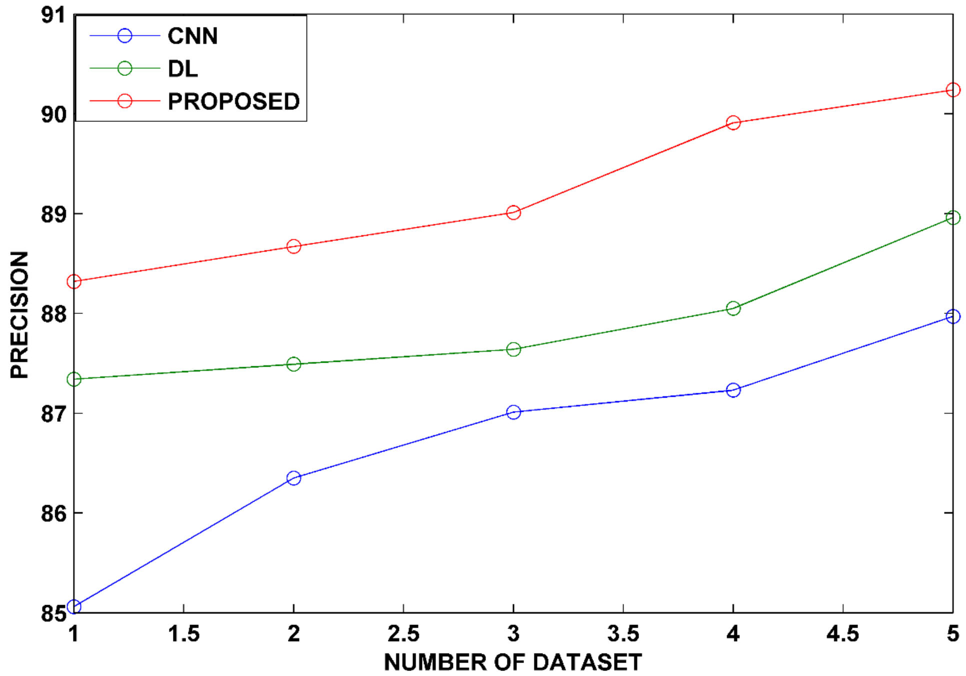

Fig 3: Comparative analysis valence emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of precision parameters. Here we observe that the precision of that proposed is better than other two techniques CNN & DL.

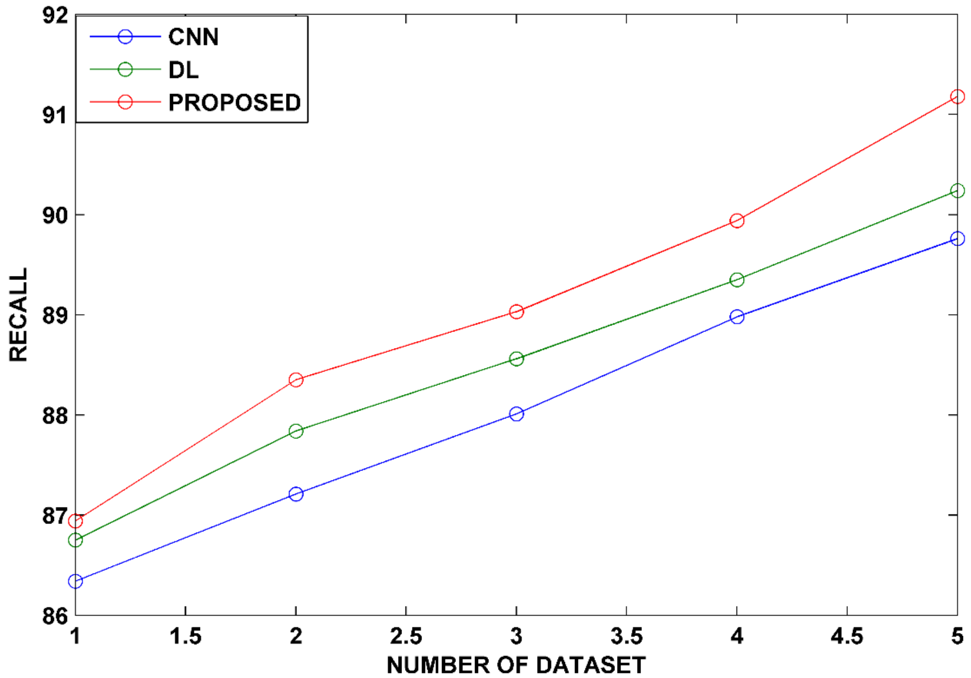

Fig 4: Comparative analysis valence emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of recall parameters. Here we observe that the recall of that proposed is better than other two techniques CNN & DL.

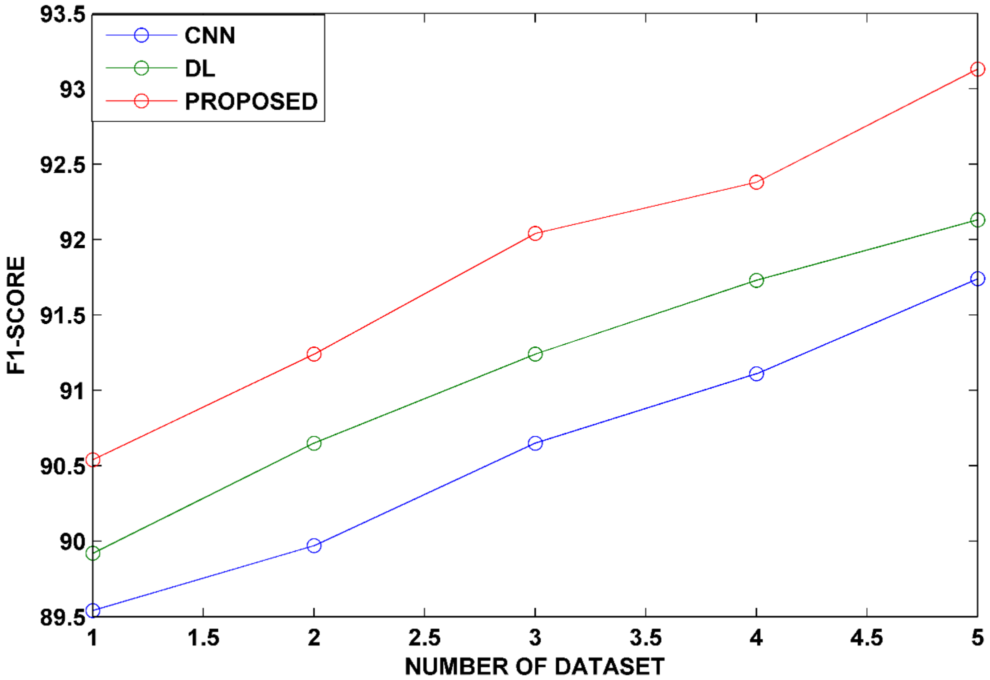

Fig 5: Comparative analysis valence emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of f-1 score parameters. Here we observe that the f-1 score of that proposed is better than other two techniques CNN & DL.

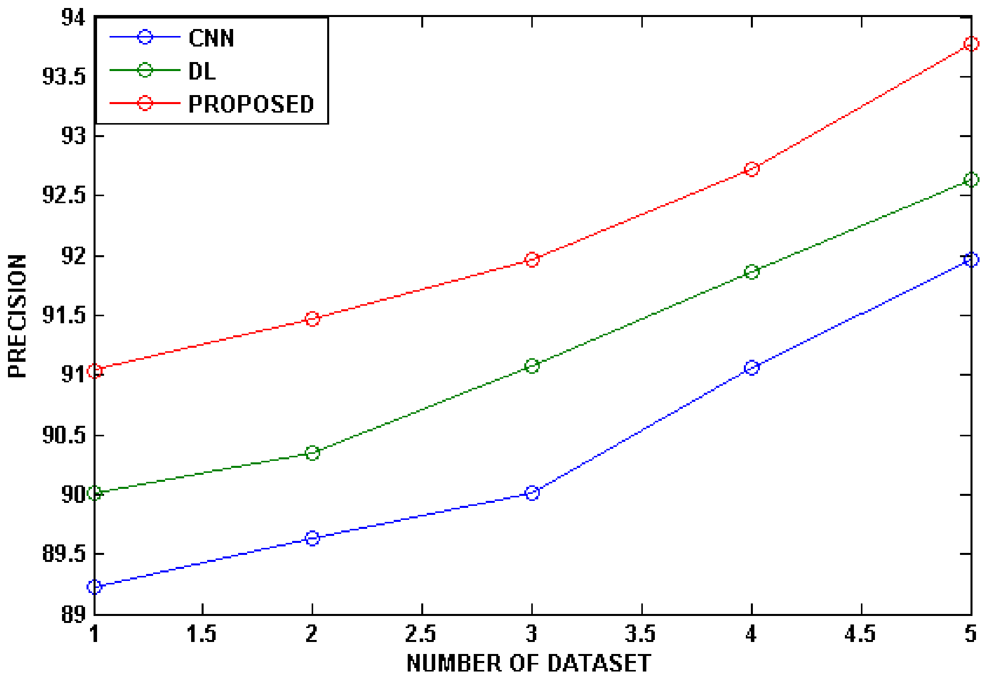

Fig 6: Comparative analysis arousal emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of precision parameters. Here we observe that the precision of that proposed is better than other two techniques CNN & DL.

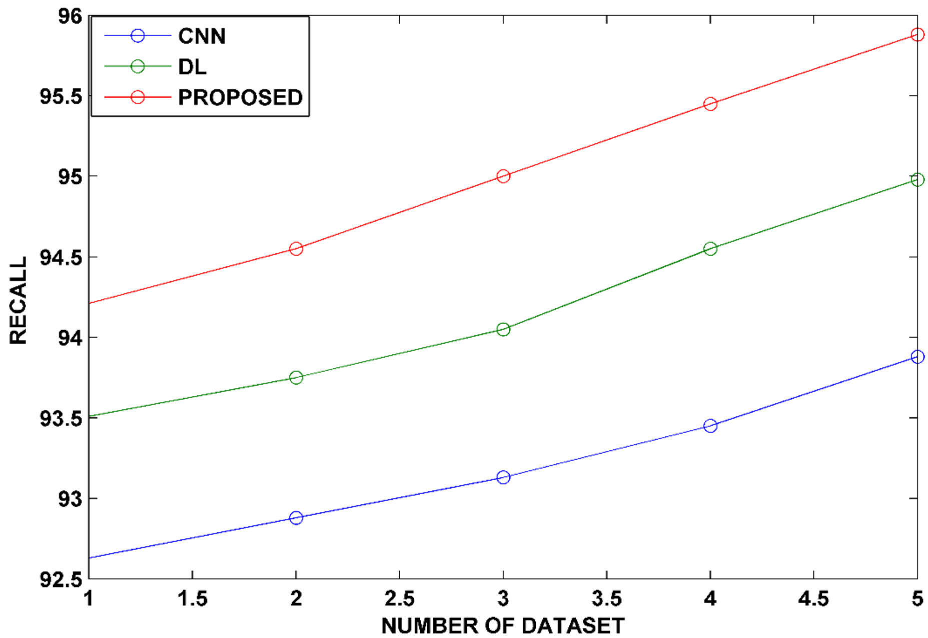

Fig 7: Comparative analysis arousal emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of recall parameters. Here we observe that the recall of that proposed is better than other two techniques CNN & DL.

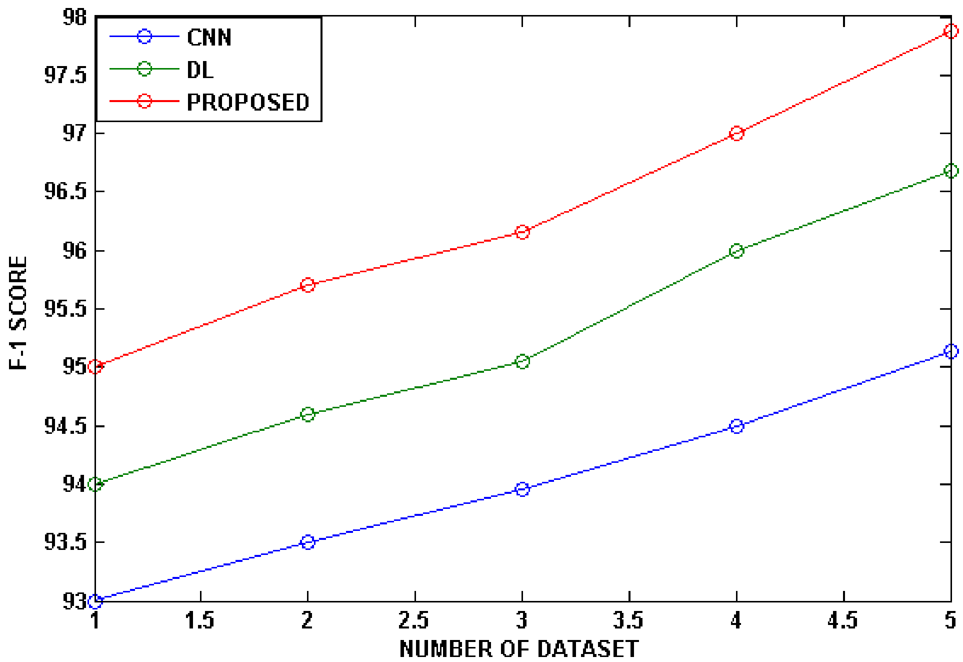

Fig 8: Comparative analysis arousal emotion of DEAP-1, DEAP-2, DEAP-3, DEAP-4, DEAP-5 Dataset using CNN, DL and Proposed model with the help of f-1 score parameters. Here we observe that the f-1 score of that proposed is better than other two techniques CNN & DL.

V. Conclusion & Future work

This paper proposed a CNN-based ensemble classifier for detecting emotion based on the EEG signals. The classification of ensemble classification process archived the following results.

1. The proposed ensemble classifier archives a maximum precision rate of 97.72 % from the Deepa dataset of different segments.
2. The proposed ensemble classifier also reduces the training time of EEG samples' sample data and reduces the voting process variation. The Deepa datasets validate detection performance in terms of aerosol and valence.
3. The applied GSO algorithm reduces the lower content of features and decreases the vector divergence of the input vector of EEG signals. The optimized data of EEG signals proceed to the designed ensemble classifier.
4. The estimation of F-measure and recall validate the results of emotion detection in compression of CNN and DL algorithm.
5. The proposed ensemble classifier compares with emotion detection algorithms such as CNN and DL. The increased ratio of detection uplifts the ratio of 2-3%.
6. The proposed ensemble classification is validated by the lower time complexity factor and increases the utilization of dedicated machines.

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