Classification of EEG signals on SEED Dataset using Improved CNN

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***Abstract* - The proposed research introduces an Improved Convolutional Neural Network (ICNN) to construct EEG-based emotion detection models. We utilized an EEG dataset of 15 subjects available from a BCMI laboratory. In our work, differential entropy characteristics obtained from multichannel EEG data are used to train the Improved CNN. The best classification accuracy is 95.67% which is significantly higher than that of the original 62 channels. The most important channels and frequency bands are identified by Improved CNN. The outcomes of our study also demonstrate the existence of neuronal signatures linked to various emotions, which are consistent between sessions and people. We contrast the effectiveness of deep and shallow models. The performance of Improved CNN is also compared with benchmark algorithms.**

Keywords- Brain Computer Interface (BCI), Electroencephalogram (EEG), Discrete Wavelet Transform (DWT), Convolutional Neural Network (CNN)

I. INTRODUCTION

The brain is a marvellous organ that manages information, governs entire bodily processes, and embodies the value of the spirit and mind. The brain is the structure inside the skull that regulates thought, mental processes, and bodily and systemic activities. It controls unconscious physical functions like digestion and heart rate as well as perception, ideas, and conscious movement. Brain regulates bodily functions; brain problems affect cognitive, memory, and reasoning. A brain and a machine can work together to create a brain-computer interface (BCI) that allows signals from the brain to control some external action, like moving a cursor or a prosthetic limb. The interface makes it possible to control an object directly from the brain via a communications channel. BCI collect and process brain signals to create commands that are then sent to output devices to perform the required tasks. BCI can be used to monitor brain activity and converts certain signal features into commands based on as an assistive, adaptive and rehabilitation technology that run on any device [1-5, 20, 23].

Another way to measure the brain activity, electroencephalograms (EEGs) use tiny electrodes affixed to the scalp. Brain activity is measured using non-invasive EEG electrodes, and commands are subsequently formed using the data. BCIs recognize changes in the EEG-measured patterns of brain activity. Then, using BCI technologies, these signals are sent to machine learning algorithms. An EEG test can be used to identify abnormal human brain waves. The electrical activity of human brain can be observed and measured using an EEG which is a reliable and affordable tool for analysing brain activity. To find problems with electrical activity of the brain, an EEG testing is used [24]. For human-machine interactions, like humanoid robots, emotional exploration is an essential one. The continuous, raw EEG data must first be filtered before being divided into brief segments that are time-locked to the relevant event codes. This is due to the fact that in order to precisely estimate and eliminate low frequencies, large data segments are required. In order to lessen and smooth out high-frequency noise that is connected with a measurement of flow, pressure, temperature, a signal must first be filtered [6-12, 23].

The EEG signal filtered using several types of filters each filter contains unique features to filter the EEG signal. The FIR filter is one of the finest options for processing EEG signals. A band-pass filter is an electrical component that discriminates against signals at other frequencies while permitting signals between two designated frequencies to pass. Feature extraction converts raw data into manageable numerical features, improving EEG signal analysis.

The EEG signal particular feature can be extract using several feature extraction techniques. The feature extraction techniques are Time Frequency Distributions (TFD), Fast Fourier Transform (FFT), Eigenvector Methods (EM), Wavelet Transform (WT), Auto Regressive Method (ARM). EEG waveforms are often categorized based on the areas on the scalp where they are recorded as well as their frequency, amplitude, and shape. EEG waveform frequency is used for the most popular classification is alpha, beta, theta, and delta [10-12].

This paper provides an overview of research methods, reviews classic segmentation approaches, describes proposed method, dataset, implementation procedure, and ideal outcomes.

II. Literature Survey

The focus of many academics over the past few decades has been on using EEG signals to predict peoples' emotional behaviours [25]. GS et al. employed the Physiological Signal (DEAP) online dataset for emotion analysis which contains both an EEG recording and an ancillary biological signal. The 32 participants watched 40 one-minute music videos at mean time EEG signals were recorded. The participant's score has been recorded for each video clip according to the quantity of valence, arousal, and dominance it contains using classification algorithms. The accuracy values for K-nearest neighbor (KNN) and Support Vector Machine (SVM) were 92.5% and 90%, respectively [1].

Kumar GS et al. have suggested an Bi-LSTM method which have used to classify positive and negative emotion for all scalp regions, including the frontal, parietal, occipital, temporal, and even all 32 electrodes, with and without deleting the outlier samples from an EEG signal. The classification accuracy is significantly increased after removing out-layered samples [2]. Iyer, A et al., have suggested convolution neural network (CNN) and long short-term memory (LSTM) method to predict the human emotions namely neutral, positive, and negative. They have used an SEED and DEAP dataset for EEG based emotion analysis [3]. Aslan, M. et al, have applied With Continuous Wavelet Transform (CWT), which is more sensitive to Time Frequency (TF) fluctuations in an EEG data. At first, EEG signals were transformed into EEG images (scalograms). Then, GoogLeNet was used to extract features from EEG images. The deep characteristics were extracted then used to classify emotions using well-known machine learning techniques. The GAMEEMO dataset was used to evaluate the suggested methodology. This study classifies emotions as either "Positive" or "Negative," respectively [4].

According to Sakalle, A. et al., the modified Long Short-Term Memory (MLSTM)-based Deep Learning model framework has been proposed for EEG signal analysis in order to determine the influence on emotion and mental health throughout pandemic. A 40-person's EEG dataset was gathered with an accuracy of 91.26% to forecast emotion and mental health. [5]. According to Liu, H. et al., the suggested model does a superior job of categorizing emotions using the DEAP dataset [6].

The music player presented in this study uses real-time brain activity analysis to give therapists physiological data that is supported by science for the purpose of identifying emotions in the experiment. The findings show that the data from 28 participants were analyzed by SVM using the two frontal midline theta and alpha associated ratios, with an accuracy rate of more than 80% for eliciting emotion. This would suggest that a variety of stimuli have the capacity to produce recognizable EEG responses at the frontal lobes that are a sign of emotion and provide a useful technique for using EEG interpretation with multimedia [7].

A unique method for identifying users' moods from electroencephalogram (EEG) signals was proposed by Sananda, P. et al. to stimulate both good and negative emotions in people, audio signals were utilized as stimuli. EEG signals were recorded utilizing the seven channels by using EEG amplifier for eight healthy people. The findings show that frontal, temporal, and parietal are the most important brain regions for recognizing good emotions, while frontal and parietal brain regions become active when negative emotions are recognized. Average SVM classification accuracy for positive emotions across all frequency bands is 84.50%, compared to QDA accuracy of 76.50%, LDA accuracy of 75.25%, and KNN accuracy of only 69.625%, and average SVM classification accuracy for negative emotions of 82.50%, compared to QDA accuracy of 72.375%, LDA accuracy of 65.125%, and KNN accuracy of only 70.50%. [8].

PSD features and pre-frontal asymmetry features were retrieved from the EEG in order to identify emotions from the data. The EEG activity for each trial was described by a set of 2184 distinctive properties. Both a DNN classifier and a Random Forest classifier were trained using these extracted characteristics. The DNN classifier performed better than the Random Forest classifier [9]. For emotion detection, electroencephalography signals from the DEAP and SEED-IV databases are taken into account. To extract the appropriate 5 frequency bands from pre-processed signals, discrete wavelet transforms were used. A few features were retrieved, including power, energy, differential entropy, and time domain. To identify the proper emotion state, a channel-wise SVM classifier and channel combiner were created. In the DEAP database, the categorization rate for four groups is 74%, 86%, 72%, and 84%; in the SEED-IV database, it is 79%, 76%, 77%, and 74% [10].

Gao, Z. et al. have used channel-fused dense convolutional network approach to analyse the EEG signal for emotion recognition.

They have employed a 1-D convolution layer to extract features from EEG data weighted combinations of temporal contextual variables and 1-D dense structures inspired by cutting-edge object categorization methods. They have captured electrode correlations along the spatial dimension. The created method can effectively extract features from noisy EEG signals while addressing temporal dependencies and electrode correlations [11].

Convolutional Neural Network (CNN) model was proposed to learn the feature and discriminate emotion of positive, neutral, and negative states of pure EEG signals. Using ResNet50 and the Adam optimizer, this model was created using the SJTU emotion EEG dataset (SEED). Before presenting the dataset to CNN model, it was splitted into training and testing segments and then randomly mixed. The results showed that model had excellent categorization skills and can more precisely identify emotions [12]. Song, T. et al, have analyzed an EEG input for emotion detection using an Dynamic Graph convolutional neural networks (DGCNN) technique. The DGCNN approach may animatedly learn innate relationship between multiple electroencephalogram (EEG) channels via the training of a neural network [13].

Tang, H. et al. have used bimodal-LSTM model that incorporates temporal information for multimodal signal emotion identification. They have adopted the Bimodal Deep de-noisingAutoEncoder Model with an EEG and eye movement features as inputs, both models are tested on SEED public dataset [14]. Hwang, S et al., have used Convolutional Neural Network (CNN) which consists of two steps. The first section maintains distance between centre electrode and other electrodes during the generation of differential entropy features. The second section teaches viewers how to use CNN's suggested three-class emotional state estimator (positive, neutral, negative). The focus of research findings given to identify the emotions of people using the 62-channel EEG recordings found in the SEED dataset [15]. Emotion detection is going to play a huge role in the future of AI and robotics. Robots that have the capacity to display and recognize emotions are already in the market to build emotional bonds between humans and robots [19]. During the literature study, it has been identified that the two datasets' SEED and DEAP have been used for their prediction. Lot of classification techniques has been studied to classify the EEG signals. Different pattern recognition methods have been applied to categories and identify particular brain signals. Rarely is an improved Convolutional neural network used to categories EEG signals. These studies help to make the researcher to deep dive into research area. In this work, DWT and Improved CNN are used to suggest a classification method for classify the EEG signals.

III. PROPOSED METHOD

The Proposed method consists of two sections i) feature extraction by Wavelet Transform (WT) and ii) classification by an improved Convolutional Neural Network.

3. 1 Feature Extraction: Wavelet Transform (WT)

A discrete wavelet transforms (DWT)-based feature extraction technique is used here. Using the wavelet transform (WT), it is possible to extract information in time-frequency space while reducing noise and keeping the key information from the original signals. DWT based feature selection is useful to identify the significant features from time-series related data.

3.2 Signal Classification: Improved Convolutional Neural Network (ICNN)

When a brain disorder arises, the EEG may display atypical electrical discharge [20]. Improved CNN runs under minimal human supervision and discovers the key elements on its own. A Deep Learning method called an Improved CNN may accept input signals, identify differences between input signals, and give various significant aspects (learnable weights and biases). A better CNN requires a lot less pre-processing compared to current classification techniques [12–18]. CNN has the ability to learn these traits and filters, in contrast to primitive approaches where filters are manually created. CNN is similar to the neurons in human brain and was designed after how the Visual Cortex is structured. The Receptive Field, a restricted region of the visual field, is the only place where individual neurons respond to inputs. The entire visual field is covered by a collection of overlapping fields [21].

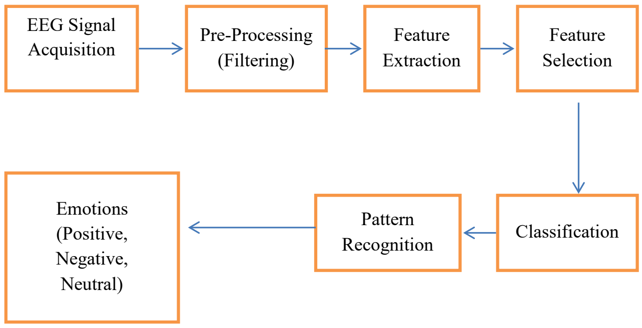

Fig. 1. Work Flow of an emotion prediction system

At first, the CNN sent features that were extracted from raw EEG. The CNN model consists of pairs of convolution pooling layers and an output layer. The network weights and filters in the convolutional layers were learned by using the back-propagation technique.

A Butterworth band-pass filter was used to extract information from an EEG signal in four frequency bands: (1–7 Hz), (8–13 Hz), (14–30 Hz), and (30–45 Hz). Following the filtering process, the data is converted into features, such as PCC, which are used as input. It's important to note that each electrode's spatial position information is included in the two-dimensional features in addition to its frequency (Tabar and Halici, 2016). The CNN organizational system is comparatively simple. Input vector can be provided by

$$x = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \quad (1)$$

where x's input vector's form is represented by m x n. At the convolution layer, filters Wk are applied to the input two-dimensional feature and are provided by

$$W_k = \begin{pmatrix} W_{11} \\ W_{21} \\ \dots \\ W_{i1} \end{pmatrix} \quad (2)$$

where x's input vector's form is represented by m x n. At the convolution layer, filters Wk are applied to the input two-dimensional feature and are provided by

$$f(\alpha) = f(W_k \times x + b_k) \quad (3)$$

where k = 1, 2,..., n, whereas n denotes the total number of filtering options available in the convolutional layer, where Wk, Ri is the weight matrix and bk is the bias value. In proposed system, the rectified linear unit (ReLU) function f serves as activation function. The weighted total is calculated by the activation function, which then adds bias to it to determine whether or not a neuron should be stimulated. The activation function's objective is to add non-linearity to a neuron's output. The definition of ReLU function is

$$f(\propto) = ReLU(\propto) = \ln(1 + e^{\propto}) \quad (4)$$

In this process, max-pooling is used since it was discovered that this function could successfully extract the maximum value from chosen values of a given feature map [12].A completely connected layer comes after final pooling layer, where output data from the pooling layer is flattened. Fully linked layers were referred to as CNN are added. Each layer's activation function in a CNN is also more efficient like ReLU. In an output layer, sigmoid and softmax are used with binary classification and multi-class classification assignments, respectively. Sigmoid can be used in hidden layer also. It ranges from 0 to 1 whereas softmax is useful for categorical values. Adadelta is used as an optimizer for the binary-classification job and binary cross-entropy, which is provided by

$$loss = -\sum_{n=1}^{N} \widehat{y_i} \log y_i + (1 - \widehat{y_i}) \log(1 - \widehat{y_i}) \quad (5)$$

where N denotes sample count, yi denotes value—a one-hot code—and yi is an output—a sigmoid—from an output layer. Adam optimizer is used for multi-class classification, loss determined by categorical cross entropy.

$$loss = -\sum_{n=1}^{N} \widehat{y_{i1}} \log y_{i1} + \widehat{y_{i2}} \log y_{i2} + \widehat{y_{i3}} \log y_{i3} \quad (6)$$

where N is sample count, yi1, yi2, and yi3 are label's values, which are type of one-hot code, and yi1, yi2, and yi3 are three outputs from output layer that employs softmax property. Model parameters are changed using back-propagation algorithm.

The gradient descent technique is used to update parameters in order to minimize an error between desired and actual output. The functions were shown by changing weight and bias.

$$W_k = W_k - \eta \frac{\partial E}{\partial W_k} \quad (7)$$

$$b_k = b_k - \eta \frac{\partial E}{\partial b_k} \quad (8)$$

the learning rate is represented by bk, the bias, and the mistake is represented by E. In Equations (5), E is equivalent to loss Eq. (6). For the performance comparison in section 3, the findings from this CNN will be served as a standard.

IV. Dataset Description

The dataset has been used in this work which came from BCMI (Brain-Computer Music Interface) laboratory. With its 62 channels, the ESI Neuro-Scan System collects EEG waves.15 subjects' EEG data are included in the SEED dataset. With an average age of 24, the data was collected from 7 women and 8 men. By obscuring their identities in order to protect their right to privacy, as BCMI has previously done, we may identify each subject by giving them a number between 1 and 15. They watched movie snippets as they collected signals. There were about four minutes in each movie segment. Each movie clip is expertly edited to maximize emotional connotations and offer cogent elicitations of emotions [20, 26]. Here is a list of the movies that were used in experiments:

Table 1: Data set description

S.No	Class Label	Movie Titles
1.	Negative	Tangshan Earthquake
2.	Negative	Back to 1942
3.	Positive	Lost in Thailand
4.	Positive	Flirting Scholar
5.	Positive	Just Another Pandora's Box
6.	Neutral	World Heritage in China

V. Implementation and Results

Each experiment consists of a total of 15 trials. In one session, there was a 5 secs hint before each clip, a 45 secs self-evaluation period, and a 15 secs rest period after each clip. Movie snippets target different emotions, participant's complete questionnaires after watching, indicating positive, negative, and neutral responses. Emotions like positive, negative, and neutral which are denoted by the numbers 1, -1, and 0 respectively. From the existing study, it has been examined that neural pattern connected to various feelings after extracting differential entropy features from five frequency bands (Delta, Theta, Alpha, Beta, and Gamma). Through time-frequency analysis, it has been discovered that there are distinct neural patterns for positive, neutral, and negative feelings in high-frequency bands. It demonstrates that the energy of beta and gamma frequency bands rise for positive feeling while it decreases for neutral and negative emotions. Neutral emotions contain more energetic alpha oscillations than negative emotions, despite the fact that the beta and gamma brain rhythms of neutral and negative emotions are identical. These discoveries give us crucial knowledge about how the brain handles emotions. The recorded frequencies have been categorized because some frequency ranges are more prevalent in particular mental states. [22]. Beta and alpha bands both reflects emotional and cognitive processing in brain, according to earlier neuroscience research [12-15]. Li and Lu et al., [16] demonstrated that by using emotional pictures as stimuli, the gamma bands of the EEG can be used to classify emotions. Their conclusions agree with the earlier findings. Participants are typically more at ease and less focused when viewing neutral cues, which stimulate alpha brain waves. Additionally, the beta and gamma responses become more active when processing happy emotions.

A. Training set-up

The above-mentioned Wavelet coefficients are parameters used by classifiers. EEG data from 15 subjects who participated in the emotion studies, each of whom completed the tests twice, spaced roughly one week apart is used. 30 experiments in total are assessed here. The test data and training data came from separate experiments session. Test data also includes data from the same experiment's other 6 sessions; the training data only includes data from experiment's 9 sessions. In order to classify the mental states for each EEG segment, we also use CNN. The fundamental principle of CNN is to use a kernel transfer function to project input data onto higher dimensional feature space that is simpler to separate than the initial feature space. To determine the ideal value, we find the parameter space 2 [-10:10] with step of 1. We build an improved CNN for deep neural networks that have two hidden levels. With a step of 50, ranges between [200:500] and [150:500], we look for an ideal number of neurons in first and second hidden layers, respectively. For trial, we settled on unsupervised learning rates of 0.9 and supervised learning rates of 0.7. Motion is also used in weight update to prevent running into local minima. Before being input into an Improved CNN, the values of detailed wavelet coefficient are adjusted between 0 and 1 by subtracting mean, dividing it by standard deviation, and then adding 0.23 to achieve improved precision [22].

B. Classification Performances

First, we evaluate how well the Discrete Wavelet Transformation feature performs across various frequency ranges. (Delta, Theta, Alpha, Beta, and Gamma). Gamma and Beta frequency bands have been working better than other frequency bands, as shown in Table I. We contrast the functionality of various elements as well. The results show that the Discrete Wavelet Transformation features, which were recovered from all frequency bands, offer superior classification accuracy. These results show that the Discrete Wavelet Transformation features perform better than other types of features [22]. The asymmetric brain activity (lateralization in left-right direction and causality in frontal-posterior direction) is significant in emotion processing as shown by the fact that the asymmetrical features (DASM, RASM, and DCAU) can achieve greater accuracy despite having significantly fewer dimensions than the PSD and DE features [17].

One of the important issues for EEG-based emotion detection is whether it is reliable and robust to recognize emotion at different periods for each individual. This problem was addressed by asking each subject to participate in the experiment twice, separated by at least one week. We also use a variety of EEG data to test the proposed theories. According to the results, the proposed models can still yield comparable prediction accuracies for each subject's two trials, despite the fact that there are clear psychological differences between people and slight conductance variations for different tests. These results also show how effective the approach is at detecting emotions at different times. Using features from five frequency bands as inputs, the details in wavelet coefficients are selected, and the accuracy of KNN, LR, CNN, and CNN is calculated using the means and standard errors. The results show that because CNN models provide greater mean accuracy and lower standard deviations, they perform better than alternative models. For the majority of subjects, CNN performs better than other conventional techniques. Some of the factors that may affect classification accuracy between participants include the subjects' educational background, sociability, and real evoked emotional state at the time of trial [22].

The target class is represented by each row, and an anticipated class produced by classifier is represented by each column. The proportion of examples from class i that were put in class j is represented by the element (i, j).

It is generally possible to identify positive emotion with high accuracy, while it is most challenging to identify negative emotion. However, the classification accuracy for negative emotion can be greatly increased by CNN. SVM works marginally better than LR and it is more accurate while predicting negative emotion in a dataset. These findings demonstrate that the deep learning approach using CNN is capable of performing feature selection tasks to weed out irrelevant features and improve categorization accuracy. While performing supervised and unsupervised learning, the effectiveness of an Improved CNN can be improved with the mixing of feature selection and feature extraction [22]. In the following workshop, we will examine in more detail the potent representations learned from deep belief networks and how they can choose the crucial frequency bands and channels through weight distributions learned from deep models. The experimental findings demonstrate that CNN methods outperform SVM, LR, and KNN in terms of accuracy. The accuracy of the achieved classification performance indicates that positive, neutral, and negative emotional neural signatures do exist.

Only tenuous support is provided for a fundamental biological viewpoint by the classification accuracy, which instead implies plausible brain architecture for emotions. Based on Zheng and Lu et al.'s [18] recommendations, we develop four unique electrode placement profiles. The four unique profiles that were the subject of this study's investigation are exhibited on four channels (F T7, F T8, and T7), six channels (F T7, F T8, T7, T8, and T P7), and nine channels (F P1, F P Z, F P2, F T7, F T8, T7, T8, and T P8). Moreover, there are 12 channels: F T7, F T8, T7, T8, C5, C6, T P7, T P8, CP5, CP6, P7, and P8. The Wavelet coefficient features are taken from these four profiles, and their performance is compared with all 62 channels combined. After training, the specified electrode set pools are reduced to reasonably small input dimensions and crucial channels are identified by deep neural networks.

The accuracies of mean CNN and standard deviations (%) for various electrode set characteristics which are displayed in Fig.2. We can see that the Wavelet features of total frequency bands enable 4 channels profile to attain an accuracy of 91.67%. Our model has obtained the best mean accuracy of 92.88% with just these 4 electrodes. Additionally, these 4 electrodes are placed in the lateral temporal region, making it simple to install them in practical situations. These findings point to the potential for creating an EEG wearable device to apply emotion recognition techniques for practical uses. The best mean precision and standard deviation for all 62 channels is 95.67%where they are the best among 4 channels.

The wavelet features achieve the greatest performance across all profiles of current EEG features as per Zheng and Lu et al., [18]. These findings support the notion that Wavelet features are better suited for emotion recognition using EEG. Comparing the 9 channels profile to 6 channels profile, which adds additional frontal electrodes FP1, FPZ, and FP2, 9 channels profile achieves slightly less than 6 channels profile by about 1 percentage point. In comparison with 62 channels, the characteristics of 6 channels, 9 channels, and 12 channels with CNNs perform better. Additionally, an original complete 62 channels with CNN obtained as higher accuracy than 12 channels profile with CNN (95.67%).

According to the findings, it is possible to decrease the number of electrodes and still we can significantly improve the performance of emotion recognition models. The optimum electrode sets will be created by removing the redundant discriminative information for emotion identification from the adjacent electrodes of the critical electrodes. Furthermore, because the brains of different people vary in their structural and functional makeup, it might have different ideal electrode sets for various people. For some individuals, certain electrodes have a significant impact on performance, but not for other subjects. Here, using the mean weight values discovered by CNNs, we seek to investigate the crucial channels across individuals.

Table 2. Calculated Wavelet co-efficient

Feature	Delta	Theta	Alpha	Beta	Gamma	Mean
4 Channels						
Approximate wavelet co-efficient	51.38	48.39	57.97	64.28	66.60	57.724
Detail wavelet co-efficient	47.84	48.52	57.62	69.89	69.20	**58.614**
6 Channels						
Approximate wavelet co-efficient	49.99	57.55	66.02	75.82	75.28	**64.932**
Detail wavelet co-efficient	42.50	44.11	53.84	60.26	61.23	52.388
9 Channels						
Approximate wavelet co-efficient	59.95	59.03	70.11	78.81	79.03	**69.386**
Detail wavelet co-efficient	44.43	47.25	58.34	68.97	66.38	57.074
12 Channels						
Approximate wavelet co-efficient	54.70	62.13	68.18	77.60	77.86	**68.094**
Detail wavelet co-efficient	46.94	46.85	59.45	69.04	70.61	**58.578**

Table 3. Obtained accuracies for 4, 6, 9 and 12 channels by CNN

Class	**Accuracies**			
No of channels	**4**	**6**	**9**	**12**
Neutral	82	84	86	90
Positive	93	95	97	97
Negative	100	100	100	100
cumulative	91.67	93	94.33	95.67

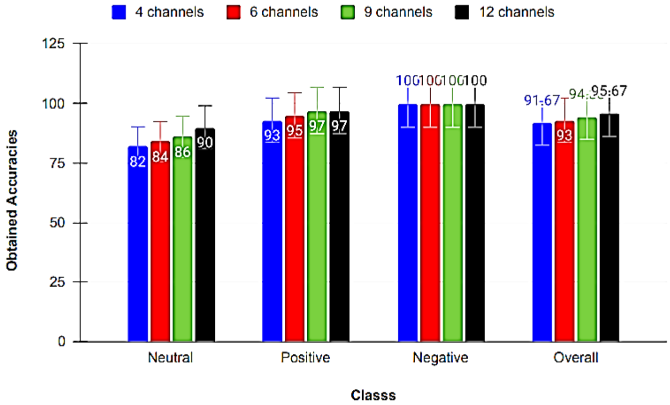

Fig. 2. Obtained accuracies for 4, 6, 9 and 12 channels by CNN

From the Fig.2 and Table. 3, it has been identified that as per number of channels increases the obtained accuracies also increases. The obtained accuracies 91.67%, 93%, 94.33% and 95.67% for channels 4, 6, 9 and 12 respectively.

VI. Conclusion

An Improved CNN model was used to design for classifying three types of emotions (positive, neutral, and negative). When 15 subjects watch emotional movie clips, 62-channel EEG data is used. After training the Improved CNN models, using the DWT features from multichannel EEG data, there is an Improved CNN-based approach to pick major critical channels and frequency bands through the weight distributions of the trained Improved CNN and have built various profiles of electrode sets. From the comparative analysis of proposed algorithms, it has been identified that the proposed Improved CNN algorithm enhances the classification accuracy. According to classification performance such as reliability, certain emotional states can be recognized by their distinct brain activity patterns.

References

[1] GS, Shashi Kumar, NiranjanaSampathila, and TanishqTanmay. "Wavelet based machine learning models for classification of human emotions using EEG signal." Measurement: Sensors (2022): 100554.

[2] Kumar GS, S., Arun, A., Sampathila, N., &Vinoth, R. (2022). Machine Learning Models for Classification of Human Emotions Using Multivariate Brain Signals. Computers, 11(10), 152.

[3] Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. Multimedia Tools and Applications, 1-14.

[4] Aslan, M. (2022). CNN based efficient approach for emotion recognition. Journal of King Saud University-Computer and Information Sciences, 34(9), 7335-7346.

[5] Sakalle, A., Tomar, P., Bhardwaj, H., &Alim, M. (2022). A Modified LSTM Framework for Analyzing COVID-19 Effect on Emotion and Mental Health during Pandemic Using the EEG Signals. Journal of Healthcare Engineering, 2022.

[6] .Liu, H., Zhang, J., Liu, Q., & Cao, J. (2022). Minimum spanning tree based graph neural network for emotion classification using EEG. Neural Networks, 145, 308-318.

[7] K. C. Tseng, B. -S. Lin, C. -M. Han and P. -S. Wang, "Emotion recognition of EEG underlying favourite music by support vector machine," 2013 1st International Conference on Orange Technologies (ICOT), 2013, pp. 155-158.

[8] S. Paul, A. Mazumder, P. Ghosh, D. N. Tibarewala and G. Vimalarani, "EEG based emotion recognition system using MFDFA as feature extractor," 2015 International Conference on Robotics, Automation, Control and Embedded Systems (RACE), 2015, pp. 1-5,

[9] Al-Nafjan, A., Hosny, M., Al-Wabil, A., & Al-Ohali, Y. (2017). Classification of human emotions from electroencephalogram (EEG) signal using deep neural network. International Journal of Advanced Computer Science and Applications, 8(9).

[10] S, Thejaswini and Kumar, Dr. K M Ravi and Nataraj,,Jhenkar L, Aditya, Analysis of EEG Based Emotion Detection of DEAP and SEED-IV Databases Using SVM (May 17, 2019). Proceedings of the Second International Conference on Emerging Trends in Science & Technologies For Engineering Systems (ICETSE-2019).

[11] Gao, Z., Wang, X., Yang, Y., Li, Y., Ma, K., & Chen, G. (2020). A channel-fused dense convolutional network for EEG-based emotion recognition. IEEE Transactions on Cognitive and Developmental Systems.

[12] Ahmad, I. S., Zhang, S., Saminu, S., Wang, L., ISSELMOU, A. E. K., CAI, Z., ...& KULSUM, U. (2021). Deep Learning Based on CNN for Emotion Recognition Using EEG Signal. WSEAS Transactions on Signal Processing, 17, 28-40.

[13] Song, T., Zheng, W., Song, P., & Cui, Z. (2018). EEG emotion recognition using dynamical graph convolutional neural networks. IEEE Transactions on Affective Computing, 11(3), 532-541.

[14] Tang, H., Liu, W., Zheng, W. L., & Lu, B. L. (2017, November). Multimodal emotion recognition using deep neural networks.In International Conference on Neural Information Processing (pp. 811-819).Springer, Cham.

[15] Hwang, S., Hong, K., Son, G., &Byun, H. (2020). Learning CNN features from DE features for EEG-based emotion recognition. Pattern Analysis and Applications, 23(3), 1323-1335.

[16] M. Li and B.-L. Lu, "Emotion classification based on gamma-band EEG," in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2009, pp. 1223–1226.

[17] W.-L. Zheng, J.-Y. Zhu, Y. Peng, and B.-L. Lu, "EEG-based emotion classification using deep belief networks," in IEEE International Conference on Multimedia and Expo (ICME), IEEE, July 2014, pp. 1–6.

[18] W-L. Zheng and B.-L. Lu, "Investigating Critical Frequency Bands and channels for EEG-based Emotion Recognition with Deep Neural Networks", IEEE Transactions on Autonomous Mental Development, 2015.

[19] E. B. Onyeulo and V. Gandhi, "What Makes a Social Robot Good at Interacting with Humans?," Information, vol. 11, no. 1, p. 43, Jan. 2020, doi: 10.3390/info11010043.

[20] SEED dataset : https://bcmi.sjtu.edu.cn/home/seed/

[21] Jinila, Y.B., Jabez, J. and Shyry, S.P., 2021, December. Virtual Self Driving Car using Improved Convolution Neural Networks. In 2021 5th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT) (pp. 215-219). IEEE.

[22] Zheng, W.L. and Lu, B.L., 2015. Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Transactions on autonomous mental development, 7(3), pp.162-175.

[23] https://bcmi.sjtu.edu.cn/

[24] Gupte, N., Patel, M., Pen, T. and Kurhade, S., 2023, April. Early detection of ADHD and Dyslexia from EEG Signals. In 2023 IEEE 8th International Conference for Convergence in Technology (I2CT) (pp. 1-5). IEEE.

[25] Zhuang, N., Zeng, Y., Tong, L., Zhang, C., Zhang, H. and Yan, B., 2017. Emotion recognition from EEG signals using multidimensional information in EMD domain. BioMed research international, 2017.

[26] Song, X., Kang, Q., Tian, Z., Yang, Y., Yang, S., Gao, Q. and Song, Y., 2020, November. Eeg-based emotion classification with wavelet entropy feature. In 2020 Chinese Automation Congress (CAC) (pp. 5685-5689). IEEE.