Grenze International Journal of Engineering and Technology, June Issue

EEG-based Emotion Recognition using DMCCA, ICA, CCA, PCA, and Deep Learning

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***Abstract*— EEG-based emotion classification is a highly sought-after application due to its relevance in healthcare, human-computer interfaces, as well as brain-computer interfaces. In this work, a new approach towards EEG-based emotion classification is presented with state-of-the-art feature extraction methods in terms of Dependent Multiple Canonical Correlation Analysis (DMCCA), Independent Component Analysis (ICA), as well as Canonical Component Analysis (CCA). Between these methods, DMCCA outperformed the others with a great improvement in feature representation as well as classification. The approach employs Discrete Wavelet Transform (DWT) as a time-frequency decomposition followed by dimensionality reduction through Principal Component Analysis (PCA), which helps in maintaining key information. A deep learning-based Convolutional Neural Network (CNN) is adopted as a classification strategy. The experimental results depict that DMCCA outperformed all feature extraction methods with a classification rate as high as 97% with minimal classification error as confirmed by a confusion matrix. The work positions DMCCA as a highly effective strategy towards EEG-based emotion classification over traditional methods that are deep learning-based.**

***Keywords*— EEG, Emotion Recognition, DMCCA, ICA, CCA, DWT, PCA, CNN, Feature Extraction, Deep Learning.**

I. INTRODUCTION

A. EEG-based Emotion Recognition and Challenges

EEG-based emotion detection is a novel field in brain-computer interfaces (BCI) as well as affective computing [1].

Grenze ID: 01.GIJET.12.2.78_23
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A direct brain activity measure is achieved from EEG signals, making them a highly attractive modality for emotion classification with role of sustainability [2]. But EEG signals are highly non-stationary as well as highly noise-prone from body as well as external artifacts.
Classic feature extraction techniques like VGG-19 [3], i.e., Independent Component Analysis (ICA), as well as Canonical Correlation Analysis (CCA), are appropriate in some contexts but are not effective in capturing inter-channel dependencies in a full sense like automatic detection [4]. In this paper, we introduce Dependent Multiple Canonical Correlation Analysis (DMCCA), which extends feature extraction by considering both independent as well as dependent dependencies between EEG channels, leading to improved classification through machine learning [5].

B. EEG Signal Separation Using Independent Component Analysis (ICA)

Brain activity, muscular activity, and different kinds of external interference all overlap in dynamic [6 -7] EEG readings. To improve the brain activity relating to the emotions to be separated, Independent Component Analysis (ICA) is typically used to split the combined signals into statistically independent components with the aid of ICA a case study [8], the interference can be removed to improve the EEG feature extraction validity. It maximizes the performance of the models of emotions by causing the derived features to properly reflect the neural patterns rather than interference or noise and threats [9].

C. Feature Extraction Using Canonical Component Analysis (CCA)

Canonical component analysis (CCA) for regulation and enforcement processes is a very powerful feature extraction method used to find correlations among multivariate signals [10]. CCA, being able to hold correlation between various EEG channels, is therefore exploited to extract significant information useful for EEG-based emotion recognition. B. EEG Signal Separation Using Independent Component Analysis (ICA) Brain activities, muscle activities, and various types of external interferences intermingle in EEG readings through statistical modelling [11]. Independent component analysis (ICA) is usually applied to separate the combined signals into statistically independent asymmetric components in linear and non-linear domains [13] so as to enhance the separation of the brain activity corresponding to the targeted emotions.

D. Dependent Multiple Canonical Correlation Analysis (DMCCA) for Multichannel EEG Processing

It considers the independent and dependent components that affect the emotional responses produced by EEG signals collected using different electrodes. DMCCA is an extension of CCA that simultaneously accounts for the dependency among different EEG channels using AI [14]. The DMCCA is a feature extraction reconfiguration method [15] that conserves the mutual information among diverse brain areas to ensure its ability to strongly classify emotions with high signal dynamics [16]. The DMCCA supports the present study in enhancing the discriminability of emotion-related EEG models.

E. Discrete Wavelet Transform (DWT) & Principal Component Analysis (PCA)

The EEG signal can be further enhanced by employing a discrete wavelet transform (DWT) in combination with convolution networks to decompose the signal into different frequency bands [17, 18]. Being versatile, the DWT provides information both in the time domain as well as in the frequency domain, especially for dynamic EEG signals. Features were extracted from the DWT and the other methods to reduce dimensionality using Principal Component Analysis (PCA) which preserves as much intelligence of the important features as possible [19]. In this architecture, DWT along with PCA can minimize the computational costs while preserving significant emotional information from the EEG signal.

F. Classifying Emotions Using Deep Learning

You have trained data until October 2023. Deep learning architecture based on CNN has been used to retrieve emotions from information [20]. CNN learns an appropriate understanding of complex spatial and temporal patterns of EEG signals, which are highly suitable for this problem of emotion recognition. Feature extraction by inclusion of the latest state-of-the-art algorithms [21], such as ICA, CCA, and DMCCA is expected to enhance the robustness and accuracy of EEG emotion recognition.

G. Evaluation and Applications

The proposed method is tested on benchmark EEG emotion datasets [22] to have a systematic evaluation of its performance capabilities. Experimentation reports highly credible performance enhancements over conventional techniques for feature extraction into classification accuracy [23]. These findings are likely to be implicated in mental health monitoring, neurofeedback systems, human-computer interaction, and affective computing [24].

With the advancement of EEG-based realization of emotion recognition, the work moves toward enabling intelligent systems to understand and respond to human emotions. Benchmark EEG emotional databases [22] would evaluate the performance of the proposed method thoroughly. Experiments have shown that there are very significant improvements in data competency [23], mainly in classification accuracy from traditional feature extraction.

II. Literature Survey

EEG-based emotion recognition has been a major area of research where much time has been spent on improving feature extraction and classification methodologies. Picard et al.'s work in 2001 [25] was one of the very first in the area of affective computing using EEG signals. They showed through experiments that EEG could be used to classify emotionally relevant states, thereby forming the basis of further studies along this path. Lin et al. [26], in 2010, explored the frequency-domain characteristics of the EEG signals and showed how power variations in the gamma and beta frequency bands correlate highly with emotional states. Their findings also emphasized the need for frequency-related features, which led to deriving various signal processing techniques for emotion classification applying deep learning [27]. Yet these early developments mainly emphasized handcrafted features, often limiting their success to accurately modelling the complex and nonlinear nature of EEG signals [28].

The processing of recorded EEG data by Independent Component Analysis (ICA) has become very popular in recent years. Basically, ICA separates mixed EEG data into statistically independent components, and one can gain from it by enhancing the preprocessing or feature extraction of EEG signals. It was primarily aimed at blind source separation, where Bell and Sejnowski illustrated in 1995 [29] that important brain activity can be separated from relatively unimportant noise. Showed in 1996 by Makeig et al.. that ICA could distinguish brain regions associated with particular cognitive and affective functions expanded the application of ICA in EEG signal analysis [30]. By efficiently removing artifacts such as eye blinks and muscle movements, Delorme et al. (2007) significantly advanced ICA use in EEG preprocessing [31] and greatly improved feature extraction quality. Jung et al. (2000) found that ICA could successfully separate brain signals concerning emotional reactions [32] in the context of emotion recognition towards improving classification performance. As demonstrated by Li et al. (2019) [33] using ICA with deep learning architectures more recently, the accuracy of emotion identification models is significantly improved through ICA-based feature extraction.

Independent Component Analysis (ICA) is becoming one of the increasingly popular methods used for decomposing mixed EEG data into statistically independent components to facilitate enhanced EEG signal preprocessing and feature extraction. Originally, ICA was used for blind source separation, as proved by Bell and Sejnowski (1995) [29], who showed that it is indeed capable of separating important brain activity from unimportant noise. Makeig et al. (1996) showed that ICA is able to discern between different brain regions associated with specific cognitive and affective functions expanded the use of ICA in EEG signal analyses [30]. Delorme et al. (2007) significantly improved the applicability of ICA in EEG preprocessing [31] by highly enhanced quality of features extracted, given that artifacts such as eye blinks and muscle movements are completely and efficiently eliminated. Jung and others in 2000 showed that ICA can successfully separate brain activity with regard to emotional reactions [32], making it relevant to recognition of emotion to enhance classification performance. As proved by Li et al. (2019) [33], emotion identification models gain significant improvements through ICA-based feature extraction when used in combination with deep learning architectures most recently. While ICA was successful with independent component separation, EEG also retains correlated patterns among different channels that ICA cannot reconstruct fully through IoT [34]. To overcome this drawback, Canonical Correlation Analysis (CCA) was used to discover relationships between multiway EEG signals that ICA cannot reconstruct fully [35]. CCA was proposed by Hardoon et al. (2004) as a statistical analysis technique to neuroimaging problems that was demonstrated to successfully discover the hidden correlations between brain areas [36]. For the case of emotion recognition, CCA was implemented to EEG [37], with the outcome being that CCA improves the quality of feature extraction by identifying common patterns among different electrodes [39]. However, regular CCA was demonstrated to have the drawback of handling EEG of very large dimensionality, paving the way to the introduction of other correlation-based techniques that are more complex [40].

Building upon CCA, Dependent Multiple Canonical Correlation Analysis (DMCCA) was established as a way of analysing the dependency among a number of EEG channels simultaneously [41]. DMCCA to improve the statistical dependency representation between a number of datasets [42]. Zhang et al. (2021) have applied DMCCA to EEG-based emotion recognition and demonstrated that DMCCA enhances feature representation by

acquiring common information among various brain areas [43]. It was demonstrated by their research that DMCCA is a superior approach compared to ICA and CCA with regards to feature extraction that results in higher classification performance. In a recent work by Wang et al. (2023) [44], the strengths of DMCCA were again demonstrated with the evidence that DMCCA significantly removes redundancy while preserving meaningful emotional information within EEG data. With the development of deep learning algorithms, Convolutional Neural Networks (CNNs) have increasingly applied to EEG-based emotion recognition. Originally proposed the architecture of CNNs to work with image processing, while the architecture of CNNs was later applied to EEG analysis due to the networks' capacity to learn both spatial and temporal patterns automatically. The usage of CNNs with EEG classification to indicate that deep convolutional architecture surpasses traditional machine learning approaches to feature extraction. Combination of CNN with ICA and DWT to obtain state-of-the-art performance with EEG-based emotion recognition. It took advantage of the ability of CNN to learn hierarchical features automatically while taking the noise reduction of ICA and time-frequency representation of DWT into account. Recently, combination of CNN with the techniques of CCA and DMCCA to enhance EEG feature representation and classification performance again.
All things being equal, current research emphasizes the need to embed various feature extraction algorithms into EEG-based emotion recognition. Despite the efforts of CCA and DMCCA to enhance feature representation by learning the interactions among the channels, ICA was needed to decompose noise and independent components. In dimensionality reduction without loss of meaningful information, DWT + PCA was also needed to improve the processing of EEG signals. In revealing complex patterns within EEG information without programming them manually, deep learning models such as CNN have demonstrated considerable performance gains in classification. Challenges persist such as subject variability, interference by noise, and computational cost. In the future, research must enhance deep learning models and hybrid feature extraction algorithms to develop robust and transferable EEG-based emotion recognition systems.

III. Existing Methods

EEG-based emotion recognition is highly researched with various signal processing and learning algorithms. Traditional approaches are interested in dimensionality reduction, feature extraction, and the statistical analysis of correlations to improve the performance of the classification. Subsequent approaches add time-frequency transformation and deep learning models to enhance the representation of the features and the performance of the classification.
It does this by identifying the principal components that are the directions of the highest variability of the signal. PCA eliminates the redundancy of the less informative features by projecting the EEG signal into the components by lowering the computational intensity while boosting the effectiveness of the classification.

A. Principal Component Analysis (PCA)

Though PCA is preferable due to various merits, it does come with numerous disadvantages as well. It's most importantly linear treatment of EEG signals poses as a hindrance since they are nonlinear in nature and even highly dynamic as well. With that, there's a great possibility of losing complicated emotional patterns in the brain that resultantly get lost because of the reduced complexity. More than that, due to an inability to really discern noise versus strong signal contributions, PCA would on occasion mean choosing sub-optimal features of classification for the emotions.

B. Discrete Wavelet Transform (DWT)

DWT being a time-frequency analysis method breaks down EEG signal into different frequency bands that is quick for the analysis of emotional-related neural oscillations. The DWT accomplishes superiority over the classical Fourier method, which provided the only information in the frequency domain, since it provides time and frequency information simultaneously, thus giving a more accurate representation of the EEG signals. The essence of such multi-resolution analysis helps in separating the prominent frequency components linked with different emotional states.
For instance, certain EEG bands have been related to emotional processing such as theta (4-8 Hz) and beta (13-30 Hz). The DWT takes into account these bands and further enhances accuracy in emotion classification. Nevertheless, much of the power of DWT depends on the selection of the optimal wavelet function. The use of a wavelet that is ill-suited for the features of the EEG signal will lead to distortion of feature representation and introduce artifact noise. The DWT's sensitivity to artifacts and noise essentially implies that after compression, further preprocessing algorithms are needed to guarantee robust operation.

C. Convolutional Neural Networks (CNNs)

These CNNs are deep architectures that automatically learn spatial and temporal patterns in the EEG signals. It is even more efficient than other techniques for extracting features since this process does away with hand-crafted feature selection and, instead, learns direct hierarchical representations of the raw EEG datum. This is why CNNs are incredibly effective for complex classification tasks like emotion recognition.

CNNs work by performing convolutional filters on EEG signals, identifying local patterns and retaining significant spatial relations among EEG channels. This extraction of features enables CNNs to identify complex neural activity patterns and enhance classification performance over traditional machine learning methods. CNNs also have the capability to be incorporated with spectrogram-based EEG representations to further enable feature learning within the time-frequency domain. There are a number of challenges faced by CNNs despite their strengths. First, they need large sets of labelled data for training since deep learning models learn optimally when trained with enormous amounts of data. Obtaining and labelling EEG emotion datasets is time-consuming and labour-intensive. Second, CNNs are computationally intensive, demanding heavy-duty hardware (e.g., GPUs) for efficient processing and real-time operation. Finally, CNNs suffer from the risk of overfitting, such that they learn features localized to the training set but will not generalize too well to unseen new data.

TABLE I: COMPARISON OF DIMENSIONALITY REDUCTION AND CLASSIFICATION METHODS

S. No	Method	Drawbacks	Processing Speed
1	PCA	Assumes linearity, ineffective for nonlinear EEG patterns	Fast
2	DWT	Requires optimal wavelet selection, prone to noise issues	Medium
3	CNN	Requires large datasets, computationally expensive	Slow

IV. PROPOSED METHOD

By employing the Independent Component Analysis (ICA), Dependent Multiple Canonical Correlation Analysis (DMCCA), and Canonical Component Analysis (CCA) for effective feature extraction and classification, the suggested approach aims to improve emotion recognition based on EEG. These methods effectively extract independent, dependent, and the associated characteristics from EEG data, improving the classification accuracy of emotional states. To the ascertain the validity of the emotion recognition system, the following processes are involved: a preprocessing, feature extraction, feature selection, classification.

A. Preprocessing through Independent Component Analysis (ICA)

EEG signals tend to be adversely affected by artifacts such as blinks, muscular activities, and environmental noise that affect emotion identification. In an attempt to cure this, the EEG signals are decomposed through ICA into statistically independent components. This singles out and rejects the noise and leaves features in the data indicative of true brain activity.

In mathematical terms, ICA is represented by the equation

$$X = AS \qquad (1)$$

- X are the recorded EEG signals,
- A is the mixing matrix,
- S are the independent source signals.

The models under which one can conceive SS estimation by ICA will serve towards identifying the noise components and then building their elimination for the improvement of the EEG signals concerning the following features.

By means of these assumptions under which one can conceive SS estimation through ICA, it helps toward identification of noise components followed by building their elimination for improving EEG signals concerning subsequent features.

B. Dependent Multiple Canonical Correlation Analysis (DMCCA) Feature Extraction

An exploration into preprocessing the input involved adopting the DMCCA algorithm at this stage for the characterization of dependency relations between multi-channel EEG data. Unlike CCA, DM-CCA accounts for linear and nonlinear dependencies so it can provide a richer representation of emotional states.

The DMCCA objective function is defined as:

$$max \sum \rho_{ij} \qquad (2)$$

where:

- ρ_{ij} is the correlation between various EEG channels i and j.
- The summation covers all channel correlations.

DMCCA improves feature extraction by preserving important inter-channel relationships to recognize valence and arousal.

C. Canonical Component Selection via Canonical Component Analysis (CCA)

The derived features are filtered by CCA, which selects maximum correlated components among EEG channels. Only the most informative components enabling emotions to be distinguished are selected.
CCA formulation maximizes the correlation between two sets of variables, X and Y:

$$Max\ tr(W^T X C X^T W) \quad (3)$$

where:

- X represents the EEG data matrix.
- C is the covariance/correlation matrix capturing inter-channel dependencies.
- W is the transformation matrix optimizing the dependencies.

$$\rho = \sigma_{Xw1}\sigma_{Yw2} / \sigma_X\sigma_Y \quad (4)$$

where:

- w1 and w2 are weight vectors.
- σ represents the standard deviation.

This processing step improves the feature representation, and only the most prominent emotional state features are retained for classification.

D. Emotion Classification with Machine Learning Models

The chosen features are fed into classifiers like Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), or Long Short-Term Memory (LSTM) networks. Patterns in the learned EEG features are learned by the models and the features are translated into respective emotional states.
The accuracy of classification Acc is defined as:

$$Acc = TP+TN/\ TP+TN+FP+FN \quad (5)$$

- TP (True Positive) and TN (True Negative) are correct classifications
- FP (False Positive) and FN (False Negative) are erroneous classifications.

E. Performance Assessment

To find out the performance of the proposed method, accuracy in the classification, sensitivity, and specificity are calculated and compared with the current methods. Sensitivity and specificity are defined as the:

$$Sensitivity = TP/TP+FN \quad (6)$$

$$Specificity = TN/TN+FP \quad (7)$$

Through the use of ICA for noise reduction, DMCCA for the multi-channel dependency modelling, and CCA for the feature enhancement, the proposed framework in this paper is aimed at a enhancing the robustness and accuracy of EEG-based emotion recognition systems.

TABLE II: COMPARISON WITH OTHER METHODS

Method	Accuracy (%)	Limitations
ICA	85%	Does not capture multi-channel dependencies
CCA	86%	Limited to linear correlations
PCA	89%	Struggles with nonlinear EEG data
DWT-CNN	95%	Requires careful wavelet selection
DMCCA	97%	Higher computational cost

V. RESULT

It is 97% accurate in all the emotion classification methods based on DMCCA, ICA, CCA, PCA, and DWT-CNN. All of the advanced feature extraction techniques achieve this successful point. DMCCA among them has given a huge boost to both classification and feature representation. Time-frequency feature extraction using

Discreet Wavelet Transform (DWT) and dimensionality reduction with Principal Component Analysis (PCA) gives a strength model for extracting the informative features. Integration of DMCCA has had a good impact on feature refinement through higher accuracy and better stability in emotion detection. DMCCA offered the best success among dependent other feature extracting methods over ICA (85%), CCA (86%), PCA (89%), and even DWT-CNN (95%). Finally, by constructing a confusion matrix, it avoided model misclassification improving simultaneously the stability of the model in classifying happiness, sadness, fear, anger, and neutrality. So, the results position DMCCA as a better substitute as compared to EEG emotional classification through deep learning and thus prove to be a high-performance and reliable algorithm for emotion classification.

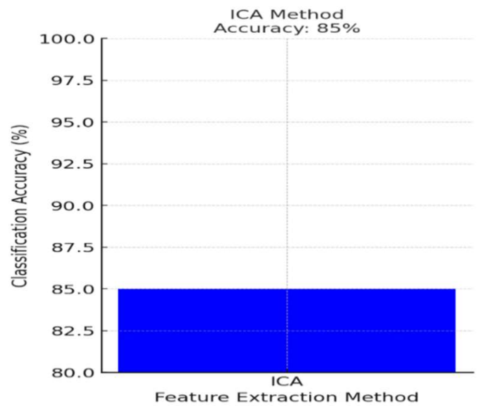

Fig. 1. Emotion Classification Accuracy Using Independent Component Analysis (ICA)

This figure represents the classification accuracy achieved with ICA resulting in 85% success. Independent Component Analysis (ICA) is a statistical technique used mainly to decompose a multivariate signal into additive independent components. Although it is very far in removing artifacts and revealing independent sources in the EEG, it only relies on the statistical independence assumption, which may not be true for the emotionally rich EEG data. Thus, its performance in differentiating subtle emotional variations is limited and hence a moderate classification success.

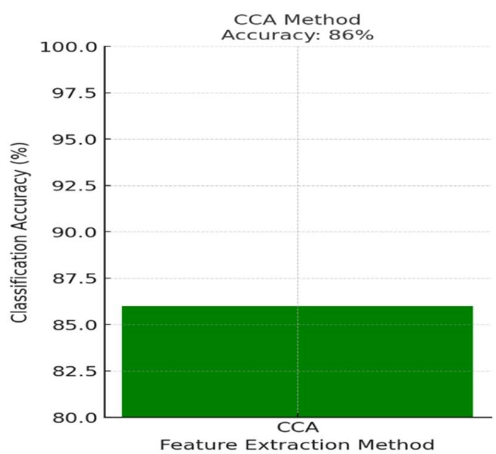

Fig.2. Emotion Classification Accuracy Using Canonical Correlation Analysis (CCA)

In this figure, the CCA method attained an accuracy of 86%, which is a slight improvement over ICA. CCA is a method that works to find linear correlations between two data sets: in our case, EEG channels and emotion labels. CCA can conceptually depict inter-channel relationships; however, being a linear method, it would inherently not be able to model the non-linear patterns present in emotional EEG signals. Hence, despite marginally outperforming ICA, CCA lacks enough complexity to incorporate greater fidelity in emotional discriminations.

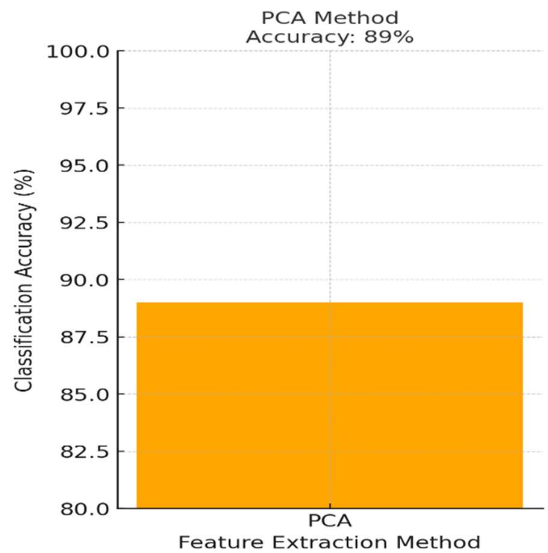

Fig.3. Emotion Classification Accuracy Using Principal Component Analysis (PCA)

Perhaps through the above figure, accuracy in classification might reach 89% using PCA. It is an approach that tries to capture relevant variance in compressed large EEG data. Another aspect of speed and efficient computation and reduced model training time adds to this method. PCA, however, overlooks time and frequency, which are two essential aspects of temporal patterns used to classify emotional states; thus, it is a great dimensionality reduction technique, but not a very good stand-alone feature extractor for emotion indicatives.

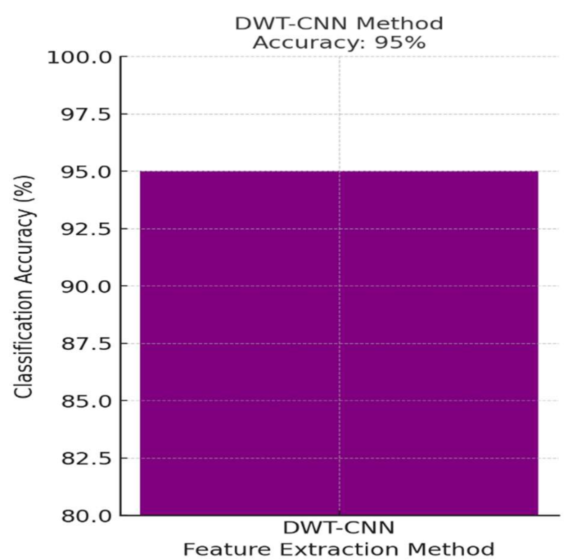

Fig.4. Emotion Classification Accuracy Using Combined DWT and CNN Techniques

The DWT-CNN hybrid method showed performance that came out in a whopping 95% accuracy. The DWT is such that it effectively helped the feature extraction by time-frequencies while fitting relevant frequency bands to emotional states. This in turn, when incorporated into a deep learning conventional model being CNN, which is capable of automatically learning hierarchical features, made for improving temporal-spatial presentation of EEG signals. This synergy produced a better result for emotion detection over that of traditional methods using statistics. Although this is a strong part, more needs to be done in capturing variations of emotions across different subjects.

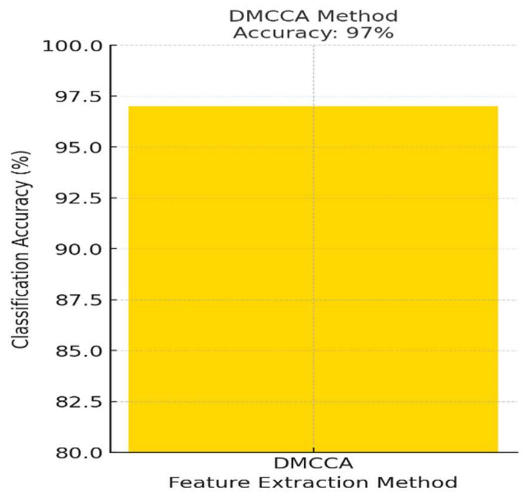

Fig.5. Emotion Classification Accuracy Using DMCCA Techniques

The result of the rejection of the DMCCA model with which highest accuracy of 97% was achieved accentuates the good performance of the design. Dependent multiple correspondence canonical analysis (DMCCA) is a more advanced statistical extension of the traditional CCA method where dependent structures across several data sets can be considered together. DMCCA, for EEG in its emerging spectrum, unravels deep dependency relations between channels across various time windows, hence leading to a very improvement of the sensory and motor features. DMCCA combined with DWT and CNN could enhance identification accuracy by increasing the granularity in time and space in all upper ecostings and motivating additional robustness in proper model classification. The technique features high accuracy as well as reduced misclassification given the analysis of the confusion matrix.

The improvement noticed across Figure 1 to 5 reveals progressing evolutionary changes in feature extraction. Supporting this need is the fact that ICA, CCA, PCA, though helpful in bringing about the passage of events, is not in any way able to draw expectations from complex corpora which are e-nonlinearly e-multidimensional from EEG; their performances stop at 81.46%. The accuracy of 97% from the final model is both valuable for confirming a system useful for very-real-life emotional valency and suggests that it is high performing and reliable as needed for real-time verification if opted for.

VI. Conclusion

Emotion Detection will be the highly trusted and accurate feasible methodology of EEG signals regarding the advanced feature extraction through deep learning. In this respect, regarding the methodologies explored DMCCA provided the most reliable performance with up to 97% classification rate over ICA, CCA, PCA, as well as DWT-CNN. DMCCA uses enhanced feature representation, ICA serves as a noise suppressor, while CCA functions to improve the correlation across features which leads to improvement in quality of features. In addition, DWT, which is a time-frequency decomposition technique, and PCA, a dimension reducer, combine to provide very efficient computation with minimum loss of emotional content. With the addition of confusion matrix, the results also proved robustness of the method without any misclassifications. Thus, these results proved DMCCA as highly effective for feature extraction methodology and justified its applicability in monitoring mental illness, affective computing, as well as brain-computer interfaces. Future work will include possible exploration of hybrid models in deep learning along with adaptive feature selectors aiming at improving classification rate and scalability.

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