Convolutional Neural Network Based Approach Towards Motor Imagery Tasks EEG Signals Classification

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***Abstract*— This paper introduces a methodology based on deep convolutional neural networks (DCNN) for motor imagery (MI) tasks recognition in the brain-computer interface (BCI) system. More specifically, the DCNN is used for classification of the right hand and right foot MI-tasks based electroencephalogram (EEG) signals. The proposed method first transforms the input EEG signals into images by applying the time-frequency (T-F) approaches. The used T-F approaches are short-time-Fourier-transform (STFT) and continuous-wavelet-transform (CWT). After T-F transformation the images of MI-tasks EEG signals are applied to the DCNN stage. The pre-trained DCNN model, AlexNet is explored for classification. The efficiency of the proposed method is evaluated on IVa dataset of BCI competition-III. The evaluation metrics such as accuracy, sensitivity, specificity, F1-score, and kappa value are used for measuring the proposed method results quantitatively. The obtained results show that the CWT approach yields better results than the STFT approach. In addition, the proposed method obtained 99.35% accuracy score is the best one among the existing methods accuracy scores.**

***Index Terms*— Electroencephalogram (EEG) signal, brain-computer interface system, motor imagery, short time Fourier transform, continuous wavelet transform, convolutional neural network.**

I. Introduction

BRAIN computer interface (BCI) is an emanating technology that deals with human brain aided control of computer or other devices. It exploits the electrical activity in the brain of the handicapped patients who have lost their abilities due to severe injuries [1]. Brain activities related to MI tasks can be captured through various acquisition methods. Among these procurement methods, Electroencephalogram (EEG) is considered as most substantial for non-invasive BCI systems, owing to its excellent temporal resolution, usability, non-invasiveness, portability, and low set-up costs. BCI intends to revive those capabilities by creating an information flow pathway from the human brain to the external device that needs to be controlled. This system utilizes the brain activity of the disabled person and tries to assist and map their sensory-motor functions. It allows the bidirectional flow of electrical information for efficient and accurate mapping. It empowers a weakened person to become independent of any external support to control any device around them.

Although it has been extensively applied in numerous applications and a handful of techniques have emerged in recent decades, but there still exists countable unresolved problems in the domain of motor imagery (MI) tasks recognition [2]. MI is one of the most frequently used mental strategy in BCI applications that deals with carrying out a motor task merely by thinking or imagining. It could be as simple as shifting of hands, legs or any other motor activity. MI stands out from the rest of the BCI systems due to its biggest advantage of independence of any body movement, which itself resolves one of the major difficulty. Classification of MI tasks provides a significant basis for modeling BCI systems for people deprived of their motor abilities and also for rehabilitation [3]. Reliable segregation of MI tasks through proper analysis of brain signal patterns are allow disabled people to easily command a device [4], [5]. Improvement in the classification performance of MI signals remains to be a critical issue for the advancement of BCI systems. The major objective of the present study is to augment an efficient technique for the automatic detection of distinct MI EEG signals. The feasibility of these systems relies on their accuracy and efficiency.

In literature, diverse signal processing methods employing time, frequency and time-frequency domain evaluation techniques have been proposed for the classification of MI tasks. Various feature extraction methods have been tested in BCI applications such as fast Fourier transform (FFT). FFT along with decision tree classifier has been used to classify epileptiform EEG signals [6]. Similarly, the utility of common spatial pattern (CSP) has been explored in various techniques. With and without regularization, it has been applied with wavelet coherence (WC) to classify two class MI tasks [7]. Features extracted using CSP have been classified using deep neural network [8]. MI tasks have been classified using aggregated regularized CSP [9]. Wavelet packet decomposition has been explored for EEG signals using higher order statistical features [10]. The wavelet transform with Wilcoxon test is used for EEG signal classification in a tabu search learning

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based fuzzy system [11]. Discrete wavelet transform (DWT) has been applied on cross-correlated (CC) signal features for classification purpose [12]. CC-LR algorithm is presented for the recognition of different MI tasks [13]. Other feature extraction schemes such as autoregressive [14], power spectral density [15], phase locking value [16] have been explored.

These aforementioned feature extraction techniques have been combined with a number of classifiers for BCI applications. A brain-machine interface (BMI) system has been designed using SVM classifier to regulate a robotic arm [17]. Temporally constrained sparse group spatial patterns (TSGSP) along with CSP has been used for classification of MI EEG [18]. In [19], CSP and particle swarm optimization (CPSO) based TWSVM classifier has been adopted in order to discriminate the MI EEG signals. An effective classifier has been accomplished using an optimized SVM based on magnetic bacteria optimization algorithm (MBOA) [20]. MI BCI systems have been dealt using one-versus-one CSP approach for feature extraction, these features have been used as input to SVM classifier [21]. In [22], SVM classifies the features extracted using wavelet coefficient measures. Adaptive extraction and categorization of subject-specific MI-based EEG patterns are done using SVM in the space-time-frequency plane [1]. The least squares SVM (LS-SVM) classifier has been used due to simpler real-time hardware implementation. Based on a clustering approach, it has been employed for the discrimination purpose [23]. Features extracted using tunable Q-wavelet transform (TQWT) have been given as input to LS-SVM for the distinction of MI activities [24]. Separation of different MI activity based EEG signals have been suggested by implementing LS-SVM on features based on analytic intrinsic mode functions [25]. Optimum allocation sampling (OAS) based approach has been presented using LS-SVM [26]. The autoregressive process based features have been used for classification using LDA and SVM [27]. Stacked LDA (SLDA) algorithm together with ensemble learning classifier has been proposed for the distinction purpose [28]. Z-score linear discriminant (Z-LDA) analysis has been evaluated for development of BCI [29].

Traditionally, machine learning techniques have been used for the classification task. But over the past few years, there has been a developing interest in the utilization of deep learning techniques. One such deep learning approach is the Convolutional neural network (CNN). It has been widely applied for image-based object detection [30], face recognition purpose [31], fingerprint liveness [32], and semantic modeling of sentences [33]. It has been explored for effective classification of amyotrophic lateral sclerosis (ALS) and normal electromyogram (EMG) signals [34]. EEG signals have been explored for accurately identification of emotion using CNN [35].

In the current framework, the utility of time-frequency representation (TFR) methods is examined on a CNN model, for the classification of the right hand (RH) and right foot (RF) MI tasks based EEG signals. The considered TFR methods are short-time Fourier transform (STFT) continuous wavelet transform (CWT). The CNN architecture that has been exploited is Alexnet. It is composed of a total of 8 layers, comprising 5 convolutional layers and 3 fully connected layers. This work adopts transfer learning where the last two layers are discharged and replaced with new layers to solve the required purpose. The effectiveness of the proposed approach is tested on publicly accessible dataset IV-A of BCI competition III. The remaining paper is structured as follows: Section II presents the dataset used, briefly explains the methods and relevant theories such as STFT, CWT, and CNN. The experimental results are depicted in Section III, followed by detailed discussion in Section IV. Ultimately, section V concludes this paper.

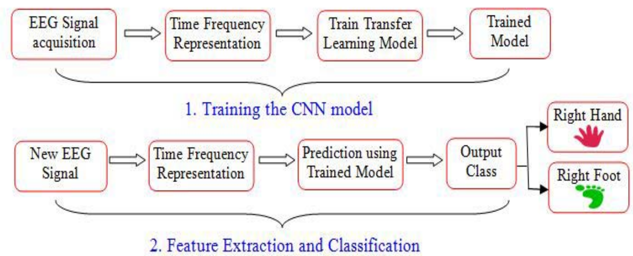


Fig. 1. Proposed approach for MI tasks classification.

II. Methodology

Fig. 1 illustrates the block diagram representation of CNN based approach for classification of MI activity based EEG signals. Relevant EEG signals are given as input to TF representations. TFR techniques allow us to represent the 1-D EEG signals as 2-D images. The TFR methods under consideration are STFT and CWT. Both of these methods allow effective characterization of the signal in both time and frequency domains. Following the transformation through TFR, MI-based EEG signals are displayed as images. These images are then fed into CNN for feature extraction and classification.

A. Dataset

The present study works upon dataset IV-A of BCI Competition-III [36]. MI-tasks of five healthy subjects namely, “aa”, “al” “av”, “aw” and “ay”, were recorded while carrying out RH and RF tasks. MI related EEG data is recorded using 118 electrodes located as per the international 10/20 system. Prior to recording, visual cues were shown to subjects for 3.5s indicating distinct MI. In total, 280 trials were taken from each subject, which composed of 140 trials each activity per subject. Later at the time of use, the unified dataset of 280 trials is segregated into training and test set for individual subjects. The sampling frequency of recorded EEG signals is 1000 Hz, further it is down-sampled to 100 Hz, followed by bandpass filtering. This was done to eliminate any contaminations and residues from the recorded EEG data [37]. The detailed information of the employed dataset is available in [36].

B. Short Time Fourier Transform (STFT)

A TF representation captures the variation of the spectral content of a signal over time. One such most basic yet sophisticated technique is STFT. It is an advanced Fourier analysis technique that presents a signal in a way that it can be completely estimated in both domains. It is primarily used for the representation of properties of non-stationary signals. STFT uses a window function to take off a portion of the time domain signal and then identifies various properties of the signal by applying Fourier transform onto the cut-out portion. It can be visualized as symmetric, identical bandpass filters evenly spaced in frequency. The STFT of a given signal $y(t)$ is estimated as follows [38]:

$$Y(t, f) = \int y(\tau)h(\tau - t)e^{-j2\pi f\tau}d\tau, \tag{1}$$

where $h(t)$ is the windowing function or a low pass filter. The resultant spectrogram is magnitude squared of the STFT, given as Spectrogram = $|Y(t, f)|^2$. The assumption is that $y(t)$ nearly stationary in the duration of the temporal window $h(t)$, and the length of the windows must be equal.

C. Continuous Wavelet Transform (CWT)

Another such effective TFR method is CWT which provides an over-complete description of a signal. It presents signals as a linear combination of principle or basis functions called wavelets, which are localized in time or space. It allows localized signal content to be analyzed. A wavelet is a finite-energy, zero-average function which indicates that it is an oscillating bandpass function. CWT is a linear operation on a time-domain signal $y(t)$ given by [39],

$$W_{(a,b)}[y(t)] = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} y(t)\phi^*\left(\frac{t-b}{a}\right)dt, \tag{2}$$

Where $\phi(t - b/a)$ is scaled and shifted version of the basis wavelet function $\phi(t)$, $a > 0$ is the scaling parameter that regulates the spread of the function, and b is the time shift parameter or the instant of time at which the signal needs to be analyzed. Thus, it is effectually identical to bandpass filtering of $y(t)$ at distinct scales. It can also be recognized as the interrelation of the input signal with a time-reversed variant of the scaled wavelet. The advantages of CWT include flexibility in alteration of window size; low frequencies can be examined over wide time windows and similarly high frequencies over narrow time windows.

D. Convolutional Neural Network (CNN)

A new subfield of machine learning, widely known as Deep learning aims at identifying various levels of distributed representations. This subset of machine learning attempts to automate the signal classification process. Deep learning algorithms are categorized as follows: CNN, Sparse Coding, Auto encoder, and Restricted Boltzmann Machines.

Inspired by the biological system, the CNN is counted as one of the most renowned technique of deep learning that involves vigorous training of multiple layers for feature extraction and classification purpose. It differs from the traditional algorithms in a manner where the network "learns" to extract features and classify, instead of manual operation. It works on transfer learning where the model trained on one task is reused for the second task. It is extremely potent and finds applications in various computer vision applications. The basic idea behind this technique is the embodiment of spatial information between pixels of a given input image of the network.

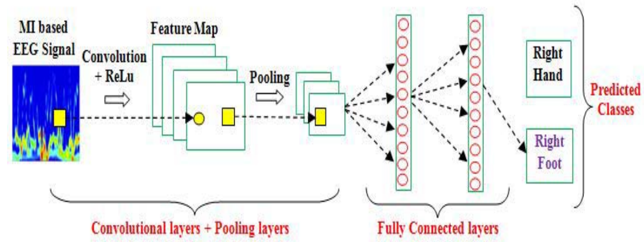


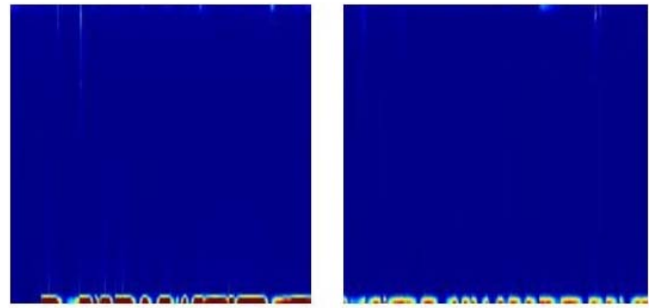
Fig. 2. Convolutional neural network architecture.

CNN architecture embodies a special combination of an input layer, multiple hidden layers, and an output layer. Each of these layers has a unique objective of processing the information received from the preceding layer. The general CNN architecture is depicted in Fig. 2. The feature detection and extraction is carried out in the hidden layers using a series of convolution and pooling procedures. These convolution and pooling layers are enclosed sequentially to formulate high-level features. Functioning of both layers is explained in brief:

- Convolution layer: This layer is composed of a series of filters, also known as kernels or edge detectors whose coefficients are tuned in the course of the training procedure. With a fixed number of filters in each layer, each individual filter is convolved transversely with the width and height of the input figure in the forward transmits. The output of this layer is a two-dimensional feature map of that filter to detect the pattern [34]. This is followed by a Rectified linear unit (ReLu) where the non-linearity is increased in the network using a rectified function.
- Pooling layer: Succeeding the convolution layer is the pooling layer where the main objective is reduction of network parameters and dimensionality of feature maps while conserving useful information. It creates a non-linear down-sampling by merging nearby values in the feature space through various operators. The number of parameters and hence, the computation in the network is reduced by minimizing the spatial size of the input, allowing the network to go deeper [34]. It is translation invariant and also regulates over-fitting. These hidden layers are succeeded by a fully connected layer that acts as the classifier for the formerly extracted features.
- Fully connected layer: It feeds forwards the neural network by converting the 2D feature map into a 1D feature vector. Scores are calculated for each category which is then converted into probabilities by a softmax layer. Lastly, the classification layer allocates a probable class or category to the object on the basis of the algorithm [34].

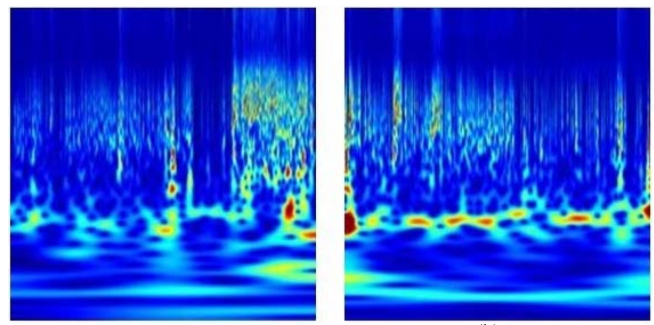
Therefore, it can be described as a hierarchical neural network composed of convolutional layers alternating with pooling layers, further succeeded by some fully connected layers. Each layer is defined and the network is trained and used continuously. These steps are repeated until the desired accuracy is obtained. The whole network is trained by adopting the conventional back-propagation algorithm where the error is back propagated to boost the classification.

With the recent surge of CNN schemes, some well-known deep learning CNN models or pre-trained networks have emerged like LeNet, ZF Net, GoogLeNet, AlexNet and many more. Transfer learning employs such pre-trained networks as reference model to train own model. It involves the transfer of previously learned knowledge from one domain to another domain, for feature extraction and classification tasks. It effectively performs deep learning by fine-tuning of model parameters. The model is trained on a new dataset with lesser number of training images as compared to formerly trained datasets. This procedure is usually much faster than the conventional training of CNN model with random weights. The most widely known out of all is AlexNet and left a huge impact on the machine learning domain. This compelling CNN architecture is formed of 8 layers that comprise of 5 convolution layers and 3 fully connected layers [40]. It is trained on ImageNet and is employed for image classification. It inputs only fixed-size (227 × 227 × 3) image. It also functions as described before, through a series of convolution and pooling operations followed by classification using a fully connected layer.



(a) (b)

Fig. 3. Spectrogram obtained using STFT for (a) Right hand and (b) Right foot respectively.



(a) (b)

Fig. 4. Scalogram obtained using CWT for (a) Right hand and (b) Right foot respectively.

III. Results and Discussion

With a motivation to propose a reliable and robust BCI system, this work focused on the effective classification of RH and RF MI tasks based EEG signals. The data used for this purpose is from dataset IV-A of BCI competition III. The present work employed two TFR methods to compare their utilities towards completing the task of discrimination of motor imageries. These two TFR methods are STFT and CWT, which are widely popular for their remarkable properties. These TF analysis methods allow to accurately evaluate the non-stationary EEG signal in both time and frequency domains. They basically transform the 1D EEG signals into 2D time-frequency images. They have already been applied in numerous problems for various purposes. In this study, their utility is explored for the distinction of RH and RF MI tasks in a BCI system.

At first, TF representation of the EEG signal is estimated using spectrograms and scalogram obtained through STFT and CWT, respectively. The spectrograms obtained using STFT method is represented in Fig. 3. This is assessed taking Hamming window under consideration. The block length is taken as 120, therefore the window function is of length 120 units. Amount of overlap allowed between adjacent blocks, i.e. the number of overlapping is limited to 100 units. Each block is zero- padded to a length of 200 units. All the simulation work is done considering sampling frequency as 100 Hz. Similarly, Fig. 4 depicts the scalogram obtained using CWT. A CWT filter bank is created using Morse wavelet. Observing the TFR of both, it can be concluded that CWT gives higher time-frequency resolution compared to STFT. STFT provides a constant resolution over the entire spectrum.

As it was mentioned earlier, both STFT and CWT images were resized to 227 × 227 × 3. These were used as input to DCNN model for feature extraction and classification purpose. In DCNN based Alexnet model, first and second convolutional layers have 96 and 256 filters of size 11 × 11 × 3 and 5 × 5 × 48 respectively. The max pooling layer follows the first two convolutional layers. Layers 3, 4 and 5 follow on similar lines. The input to first fully connected layer is a 13 × 13 × 128 vector which is multiplied with a matrix to give an output of 1 × 2048 configuration. Layers 7 and 8 follow on similar lines. Transfer learning is employed to fine-tune the pre-trained network Alexnet. The last two layers are discharged for adaptation and replaced with new layers to learn features unique to the used dataset. They are fine-tuned for MI tasks based EEG signal recognition where the number of classes is two (RH and RF). Then, the features abstracted from the trained images are used to classify the test images. 80% of input data has been utilized for training the Alexnet model and the residual 20% has been employed for testing the fine-tuned model. The learning rate is set to 0.0001 for fine-tuning of the DCNN model. The maximum epoch is set to 15 and total 1830 iterations were carried out for the training procedure. Thus, 122 iterations are performed per epoch. Fig. 5 shows the progress of fine-tuned Alexnet model with CWT images. The first row signifies the deviation of the accuracy against iterations whereas, the second row presents the loss deviation against iterations.

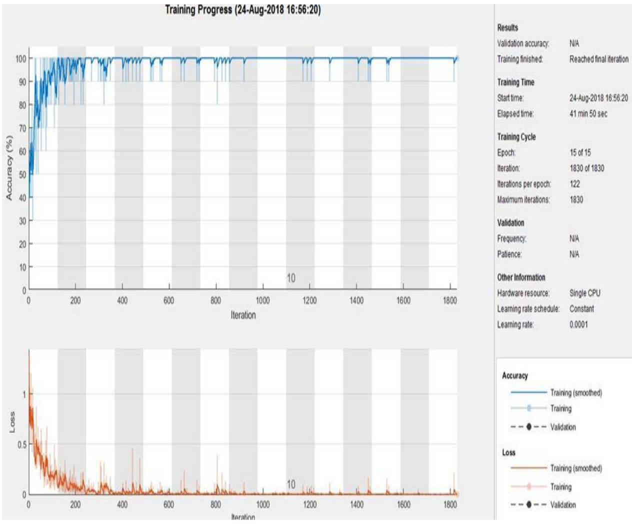


Fig. 5. The training progress of fine-tuned Alexnet model with CWT images.

TABLE I
THE CONFUSION MATRICES OF TFR METHODS

MI-Tasks	STFT		CWT	
	RH	RF	RH	RF
RH	TP=165	FP=0	TP=165	FP=0
RF	FN=4	TN=138	FN=2	TN=140

A. Performance of TFR Methods

Table I demonstrates the confusion matrices obtained using TFR methods. For these confusion matrices, the classification performance measures of both TFR methods are shown in Table II. The performace parameters are defined as:

$$Accuracy(\%) = \frac{TP + TN}{TP + PN + FP + FN} \times 100 \quad (3)$$

$$Error(\%) = \frac{FP + FN}{TP + PN + FP + FN} \times 100 \quad (4)$$

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100 \quad (5)$$

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100 \quad (6)$$

$$F1 - Score = \frac{2Precision \times Recall}{Precision + Recall} \quad (7)$$

$$Precision = \tfrac{TP}{TP+FP}; Recall = \tfrac{TP}{TP+FN}$$

$$K = \frac{TP \times TN - FP \times FN}{\sqrt{((TP + FP)(TP + FN)(TN + FP)(TN + FN))}} \quad (8)$$

where TP and TN represents the total number of correctly detected positive and negative events respectively. Similarly, FP and FN represents the total number of erroneously detected positive and negative events respectively. Table II concludes that CWT yields better results as compared to STFT. The classification accuracy obtained using CWT is 0.66% higher as compared to STFT. Also, the error or the misclassification rate using CWT is mere 0.65% which is almost negligible. In comparison, the misclassification rate using STFT is much higher at 1.3%. Thus, CWT is more accurate and effective for the task of discrimination of RH and RF MI EEG signals. Though the specificity obtained using both the techniques is 100%, the sensitivity achieved is again better using CWT. It is 1.17% higher than the value using STFT. Therefore, it can be definitely concluded that though both are equally good for classification of RF tasks, CWT is more reliable for identification of RH tasks. The F1-Score value obtained using CWT is 0.994 and the value obtained using STFT is 0.988. The kappa value achieved using STFT is 0.9798 which is 0.0071 lower than CWT. The performance of CWT is better in comparision to STFT for classification. CWT gives more satisfactory results and Table II evidently concludes that CWT is more reliable and effective choice for the accurate identification of RH and RF MI tasks based EEG signals.

TABLE II
CLASSIFICATION PERFORMANCE OF BOTH TFR METHODS

Parameters	STFT	CWT
Accuracy (%)	98.7	**99.35**
Error (%)	1.3	0.65
Sensitivity (%)	97.63	98.80
Specificity (%)	100	100
F1-Score	0.988	0.994
Kappa value (K)	0.9798	0.9869

TABLE III
CLASSIFICATION PERFORMANCE COMPARISON WITH RECENTLY PRESENTED SAME DATASET METHODS

Authors and year	Methods	Classifier	Accuracy(%)
Proposed Approach	CWT	CNN	**99.35**
Taran et al. [2018] [26]	EMD	LS-SVM	97.56
Taran et al. [2018] [25]	TQWT	LS-SVM	96.89
Kevric et al. [2017] [10]	MSPCA, WPD, HOS	k-NN	92.8
Siuly et al. [2016] [3]	OA	NB	96.36
Siuly et al. [2015] [27]	OA	LS-SVM	96.62
Verma et al. [2014] [12]	DWT	LS-SVM	96.1
Zhang et al. [2013] [30]	Z-score	LDA	81.1
Suily et al. [2013] [13]	CC	LR	91.79
Siuly et al. [2012] [2]	CC	LS-SVM	95.72
Siuly et al. [2011] [24]	CT	LS-SVM	88.32
Lu et al. [2010] [9]	R-CSP with aggregation	R-CSP	83.9
Ince et al. [2009] [1]	CS	SVM	96

B. Performance Comparison

To further inspect the efficiency of the suggested scheme, it was compared against various contemporary methods previously given using same base dataset. Table III shows a comparative performance analysis of the present approach with previous methods. Classification accuracy is established as the base parameter for comparison. Table III shows numerous prominent methods that have already been reported for BCI applications. Techniques such as EMD, DWT, TQWT, R-CSP, and OA were employed to effectively identify the two classes. Also, various classification schemes such as R-CSP, LDA, NB, SVM, and LS-SVM have been utilized. The results obtained using these techniques have been listed in Table III. As seen in Table III, the compared methods produced various accuracy scores in the range of 81.1% and 97.56%. Especially, most of the compared methods achieved accuracy scores around 96%. Until our work, the Taran *et al.* [25] method produced the highest accuracy score where the authors used the EMD and LS-SVM techniques. In another work of the Taran and Bajaj [24] used the TQWT and LS-SVM techniques and obtained 96.89% accuracy score. Siuly and Li [26] and Siuly *et al.* [3], Verma *et al.* [12], and Ince *et al.* [1] obtained accuracy scores 96.62%, 96.36%, 96.1% and 96%, respectively. The above-mentioned works used SVM and LS-SVM techniques in the classification stage of their works.

In comparison with such well-known methods, our approach seems to be ahead in the task of discriminating MI tasks-based non-stationary EEG signals. It has outperformed other methods by achieving the highest classification accuracy of 99.35%. It surpasses various other significant combinations of feature extractors and classifiers. Table III establishes the robustness and potency of the proposed method. Thus, utilization of T-F transformations for reconstruction of EEG signals into images combined with deep learning AlexNet model empowers as a robust approach. It is highly productive and can be definitely employed for the betterment of disabled people.

IV. Conclusion

This paper investigates the performance of the DCNN on MI-tasks EEG signals classification. To this end, the transfer learning approach is adopted where the pre-trained AlexNet model is used. In the DCNN structure, both feature extraction and classification are carried out. The proposed method uses two T-F approaches for conversion of input EEG signals into images. The results obtained with the CWT technique are better than that obtained using the STFT method. This indicates that the CWT method provides a better representation of EEG signals in the T-F domain as compared to the STFT method. In other words, the CWT images may have more distinctive features for EEG signals than the STFT method. The obtained results show that the proposed methodology is more effective for MI-tasks classification as compared to existing methods. In future, various T-F methods can be used for transforming the input EEG signals into images. The utility of VGGNet, GoogleNet and ResNet models can be explored in our future works.

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