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EEG based multi-class seizure type classification using convolutional neural network and transfer learning

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ABSTRACT

Recognition of epileptic seizure type is essential for the neurosurgeon to understand the cortical connectivity of the brain. Though automated early recognition of seizures from normal electroencephalogram (EEG) was existing, no attempts have been made towards the classification of variants of seizures. Therefore, this study attempts to classify seven variants of seizures with non-seizure EEG through the application of convolutional neural networks (CNN) and transfer learning by making use of the Temple University Hospital EEG corpus. The objective of our study is to perform a multi-class classification of epileptic seizure type, which includes simple partial, complex partial, focal non-specific, generalized non-specific, absence, tonic, and tonic–clonic, and non-seizures. The 19 channels EEG time series was converted into a spectrogram stack before feeding as input to CNN. The following two different modalities were proposed using CNN: (1) Transfer learning using pretrained network, (2) Extract image features using pretrained network and classify using the support vector machine classifier. The following ten pretrained networks were used to identify the optimal network for the proposed study: Alexnet, Vgg16, Vgg19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101. The highest classification accuracy of 82.85% (using Googlenet) and 88.30% (using Inceptionv3) was achieved using transfer learning and extract image features approach respectively. Comparison results showed that CNN based approach outperformed conventional feature and clustering based approaches. It can be concluded that the EEG based classification of seizure type using CNN model could be used in pre-surgical evaluation for treating patients with epilepsy.

1. Introduction

Epileptic seizures are caused by a disturbance in the electrical activity of the brain, which is classified into focal, generalized, and unknown (Ko, 2017; Schachter & Sirven, 2017). Accurate classification of epileptic seizure type plays a crucial role in the treatment and disease management of epilepsy patients (Roy, Asif, Tang, & Harrer, 2019). Focal seizures start on one side of the brain and depending on the patient level of awareness during a seizure, it is again classified as simple partial and complex partial seizures (Fisher et al., 2017; Scheffer et al., 2017). Generalized seizures affect both sides of the brain at the same time and again divided into absence, tonic, atonic, clonic, and tonic–clonic, myoclonic seizures (Schachter & Sirven, 2017). Generalized seizures are classified based on motor symptoms and non-motor symptoms that involve movement (Fisher et al., 2017; Schachter & Sirven, 2017; Scheffer et al., 2017). Motor symptoms include jerking movements (clonic), muscles becoming tense or rigid (tonic), muscles becoming weak or limp (atonic), and brief muscle twitching (myoclonic) (Fisher et al., 2017; Schachter & Sirven, 2017; Scheffer et al., 2017). Unknown seizures are the one when the beginning and where the seizure starts is not known (Fisher et al., 2017; Scheffer et al., 2017).

Epileptic seizure type affects the choice of drugs and patient safety (Roy et al., 2019). Most of the work reported in the literature focused on the application of machine learning towards automated seizure detection. There is a huge demand to extend the application of machine learning especially convolution neural networks (CNN) for multi-class seizure type classification. As we know that manual inspection of long-term electroencephalogram (EEG) recordings, lasting several days or weeks is a time-consuming task. Special attention is required to develop an automated algorithm for classification of multi-class seizure type. Therefore, in this study, we have classified seizure type using

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EEG alone without using motor symptoms, level of awareness and video EEG. Such automated procedure may help the neurological community to improve clinical decision making and identify the optimal treatment for epilepsy patients.

The application of CNN towards the classification of epileptic seizures have been implemented in recent studies (Acharya, Oh, Hagiwara, Tan, & Adeli, 2018; Achilles, et al., 2018; Birjandtalab, Heydarzadeh, & Nourani, 2017; Truong, et al., 2017; Ullah, ul Haq Qazi, & Aboalsamh, 2018; Zhou et al., 2018). In a recent study by Acharya et al. (2018), a 13-layer deep CNN showed an accuracy of 88.67% using the University of Bonn database. Plot EEG image-based study using CNN showed a true positive rate of 74.0% between seizure and non-seizures EEG activities (Emami, et al., 2019). Seizure prediction using intracranial and scalp electroencephalogram signals achieved a sensitivity of 81.4%, 81.2%, and 75.0% using the Freiburg Hospital intracranial EEG dataset, the Boston Children's Hospital-MIT scalp EEG dataset, and the American Epilepsy Society seizure prediction challenge dataset respectively (Truong, et al., 2018). Neonatal seizure detection using deep CNN with 26 neonates achieved the seizure detection rate of 77.0% (Ansari, Cherian, Caicedo, & Naulaers, 2018). Signal transforms using empirical mode decomposition and classification using CNN showed an accuracy of 98.9% when classifying between focal and non-focal signals (San-Segundo, Gil-Martín, D'Haro-Enríquez, & Pardo, 2019). In the same study, an accuracy of 99.5% for classifying non-seizure vs. seizure recordings, 96.5% between healthy, non-focal and seizure recordings, 95.7% when classifying healthy, focal and seizure recordings was obtained. A CNN based model showed the highest accuracy of 96.7% and 97.5% using the Freiburg and CHB-MIT databases respectively (Zhou et al., 2018). Another study using the University of Bonn database was proposed using pyramidal 1-dimensional CNN for binary classification of seizure vs. non-seizure and normal vs. ictal (Ullah et al., 2018). Similarly, an F-measure of 95.0% was achieved between the classification of seizure and non-seizure using deep neural networks (Birjandtalab et al., 2017). Video-EEG recordings were classified using CNN showed the area under the curve of 78.33% for real-time seizure detection (Achilles, et al., 2018). A recent study using machine learning for 7-class seizure type classification showed an F1 score of 0.907 without using non-seizure EEG signals (Roy et al., 2019). The sensitivity of 30.83% and specificity of 96.86% was achieved using deep CNN architecture on the TUH database (Golmohammadi, et al., 2017). Seizure detection was performed using the robust features learned from images based representation of EEG spectrogram in three frequency bands (0–7, 7–14, and 14–49 Hz) (Thodoroff, Pineau, & Lim, 2016). Internet of Things based optimized deep learning for seizure prediction was proposed using EEG big data (Hosseini, Pompili, Elisevich, & Soltanian-Zadeh, 2017).

Adaptive structure of a multi-layer back-propagation network was proposed for automatic epileptic seizure detection using five epilepsy patients EEG data (Weng & Khorasani, 1996). A reliable classifier architecture was obtained by applying fast Fourier transform (FFT) and auto-regressive based features to wavelet neural networks classifier (Subasi, Alkan, Köklükaya, & Kiymik, 2005). A supervised multi-spiking neural network architecture showed a classification accuracy in the range of 90.7%–94.8% which was better than single-spiking neural network (Ghosh-Dastidar & Adeli, 2009). A continuous neural networks based model showed a maximum correct classification percentage of 97.2% for two-class problem (Alfaro, Argüelles-Cruz, & Oria, 2016). A review was given on recent supervised and unsupervised methods to train deep spiking neural networks and compared them in terms of accuracy and computational cost (Tavanaei, Ghodrati, Kheradpisheh, Masquelier, & Maida, 2018).

Other than CNN, recent studies have focused on automated detection of epileptic seizures using different feature extraction methods and machine learning algorithms. The features like log energy and norm entropy (Aydın, Saraoglu, & Kara, 2009; Raghu & Sriraam, 2018; Raghu, Sriraam, & Kumar, 2016; Sriraam & Raghu, 2017), sigmoid entropy (Raghu, et al., 2019), matrix determinant (Raghu, Sriraam, Hegde, & Kubben, 2019), approximation entropy (Srinivasan, Eswaran, & Sriraam, 2007), sample and phase entropy (Acharya, et al., 2012), and permutation entropy (Li, Yan, Liu, & Ouyang, 2014) have been explored for seizure detection. Multi-features based classification of focal and non-focal EEG signals was performed using the support vector machine (SVM) classifier (Raghu & Sriraam, 2018; Sriraam & Raghu, 2017). Optimal configuration of multi-layer perceptron was performed using different transfer functions, training functions and mean square error for classification of epileptic seizures (Raghu & Sriraam, 2017).

It is clear from the literature that no successful studies (in terms of classification results) have been proposed for the classification of multi-class seizure type in the presence of non-seizure EEG signals. Therefore, this study suggests a CNN based framework using transfer learning and extract image features using pretrained networks for classifying the EEG derived seizure type. To the best of the author's knowledge, this is the first of its kind study using deep learning for classification of multi-class seizure type.

2. Methodology

2.1. EEG recordings

The multi-class seizure type classification was implemented using the EEG signals collected from the Temple University Hospital (TUH) open-source database (Obeid & Picone, 2016). This scalp EEG signal recordings were recorded according to the International 10–20 system electrode placement at a sampling rate of 250 Hz. The TUH database consists of simple partial seizure (SP), complex partial seizure (CP), focal non-specific seizure (FN), generalized non-specific seizure (GN), absence seizure (AB), tonic seizure (TN), tonic–clonic seizure (TC), and myoclonic seizures. In our study, we ignore the myclonic seizures because of its very low count. The recordings consist of following 19 unipolar channels EEG: Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, and O2. The EEG recordings were annotated with different type of seizures based on Electrographic, Electroclinical, and Clinical manifestations (Database, 2016). The description of the TUH database used in the study is summarized in Table 1. The EEG files other than seizure type labels were considered as non-seizure (NS) and not all the NS events were considered for the study due to the imbalance data challenge of CNN. For the experiment, 83.46 h of EEG data from 352 subjects were considered for the study. The subjects suffering from more than one type of seizures were excluded from the study.

2.2. Preprocessing

The EEG signals were passed through a bandpass filter with a cut-off frequency of 0.1–44 Hz. Since CNN expects 2-dimensional input for its analysis, the EEG signals were converted into an image using short-time Fourier transforms (STFT). The following specifications were set to compute the STFT: Kaiser window of length 63 with a shape parameter of 1, 75% overlap, and an FFT length of 256. The spectrogram of all the 19 channels was vertically concatenated to form the final image (refer to Figs. 1 and 2). In order to overcome the imbalance dataset challenge of CNN, we have used an overlap technique to produce balanced samples or images for the training phase (Truong, et al., 2017).

Table 1
EEG database details used for the proposed study.

Seizure type	Description	Number of patients	Seizure events	Duration (h)
SP[a]	Partial seizures during consciousness; Type specified by clinical signs only	18	63	1.2
CP[a]	Partial seizures during unconsciousness; Type specified by clinical signs only	31	210	8.2
FN[b]	Focal seizures which cannot be specified by its type	63	542	22.56
GN[b]	Generalized seizures which cannot be further classified into one of the groups below	75	231	12.5
AB[a]	Absence discharges observed on EEG; the patient loses consciousness for a few seconds (Petit Mal)	21	63	1.3
TN[a]	Stiffening of the body during a seizure (EEG effects disappears)	19	29	1.3
TC[a]	At first stiffening and then jerking of the body (Grand Mal)	15	25	0.8
NS[a]	EEG without any type of seizure events	110	540[c]	35.6

Manifestation: [a]Electroclinical, [b]Electrographic and [c]Number of Non-seizure events.

2.3. Convolutional neural network

CNN has been found to be an ideal for image-based classification due to its self-feature learning capability and excellent classification results on multi-class classification problems. A CNN consists of a convolution layer (Conv) with rectified linear unit (ReLU) activation function, pooling layer (Pool) and batch normalization. Further, at the final layers, it consists of fully connected (fc), drop out, softmax and classification output layers. Conv layer have filters which detect different patterns in image (spectrogram) such as edges, shapes, textures, and objects. In this study, ten pretrained CNN models, namely Alexnet, Vgg16, Vgg19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 were used to identify the best model for the proposed 8-class problem (Deeplearning, 2019; Shelhamer, 2017; Simonyan & Zisserman, 2015). The proposed method was evaluated using the following two methods: (1) Transfer learning using pretrained network, (2) Extract image features using pretrained network.

2.3.1. Transfer learning using pretrained network

Transfer learning is the process of taking a pretrained deep learning network and fine-tuning it to learn a new task (Szegedy, et al., 2015). Fig. 1 shows the flow of the multi-class seizure type classification based on the transfer learning using pretrained network. Transfer learning was performed by using the following steps:

1. Create the spectrogram image data using EEG signals.
2. Choose a pretrained network.
3. Replace the final layers with new layers adapted to the new data set.
4. Specify the new number of classes (in our study 8-class) in training images.
5. Resize images, specify training options (Solver name or training options, initial learning rate, number of epochs, mini-batch size, validation data, and validation frequency) and train the network.
6. Test trained network by classifying test or validation images.

Table 2 shows ten different pretrained networks used for the study (Deeplearning, 2019) along with network depth, number of layers, required image input size, and final three layers replaced for the each pretrained networks. In order to identify the suitable model, the learning rate (LR) was varied as 1e-3, 1e-4, 1e-5 and 1e-6 and three solvers were used, namely stochastic gradient descent with momentum (sgdm), root mean square propagation (rmsprop), and adaptive moment estimation (adam) optimizer.

2.3.2. Extract image features using pretrained network

In this method, we have used a pretrained network as a feature extractor by using the layer activation's as features and classified using the SVM classifier (Networks, 2019). Feature extraction is the easiest and fastest way to use the representational power of pretrained deep networks because it only requires a single pass through the data. The flow of extract image features using pretrained network approach is depicted in Fig. 2. In this method, features were extracted from all the layers and classified using the SVM classifier for all the ten pretrained networks (Networks, 2019). In pretrained networks, deeper layers contain higher-level features, which are constructed using the lower-level features of earlier layers (Networks, 2019; Zeiler & Fergus, 2013). Further, earlier layers typically extract fewer, shallower features, have the higher spatial resolution, and a larger total number of activation's (Networks, 2019; Zeiler & Fergus, 2013).

2.4. Classification methodology

In both the methods, the dataset was divided into 70% and 30% for training and testing phase respectively. The SVM classifier was trained using a radial basis kernel function. The performance of the model was assessed using classification accuracy. The experiment was repeated for 10 times and average results were reported.

3. Results

In this section, we discuss the classification results obtained using both transfer learning and extract image features approach. Fig. 3 depicts the classification accuracy obtained using transfer learning approach. The experiment was conducted using different solvers and LR. The highest accuracy of 77.66% (LR = 1e-4), 76.60% (LR = 1e-5), 74.47% (LR = 1e-4) was achieved using sgdm, rmsprop, and adam solvers respectively using Alexnet model. The rmsprop using LR of 1e-5 showed the highest accuracy of 67.02% and 65.96% using Vgg16 and Vgg19 respectively. Squeezenet outperformed with LR of 1e-4 against other LR's using all the three solvers. Googlenet showed the highest accuracy of 74.74% (LR = 1e-3), 78.72% (LR = 1e-4), and 82.85% (LR = 1e-4) using sgdm, rmsprop, and adam solvers respectively. Inceptionv3 network

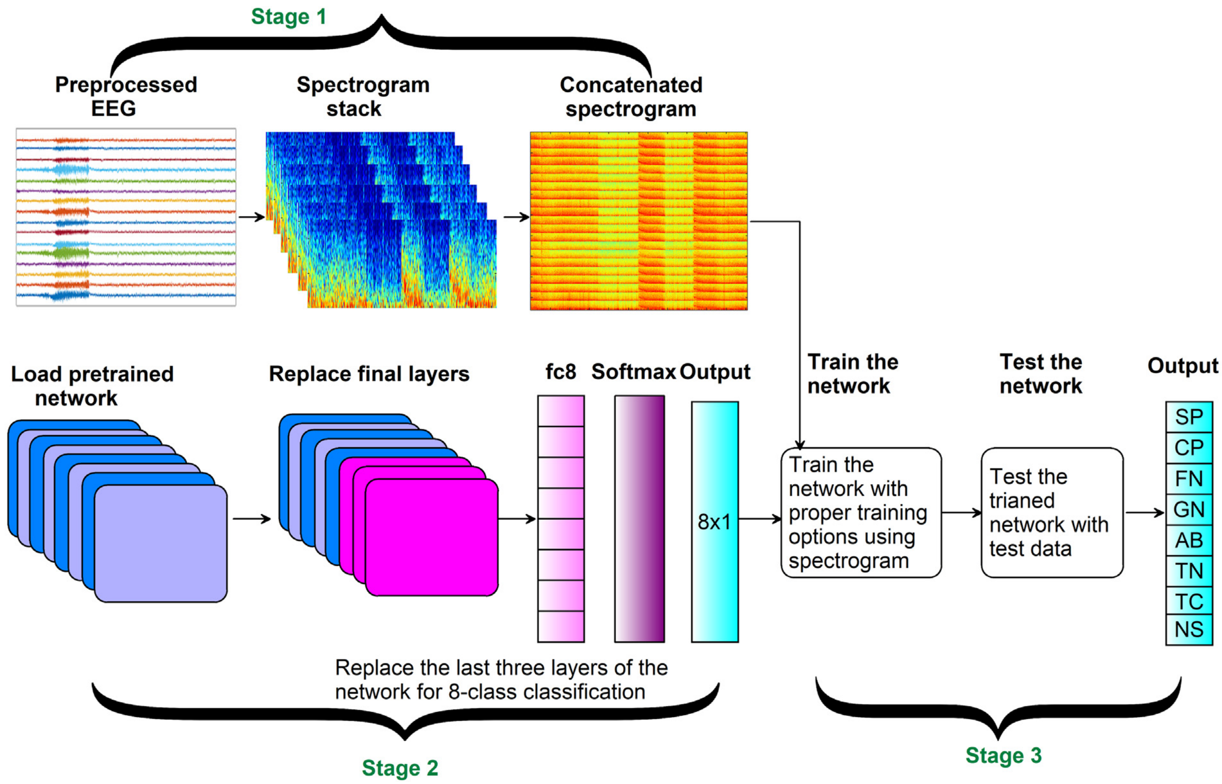

Fig. 1. Flow of the multi-class seizure type classification based on transfer learning using pretrained network. **Stage 1:** Generation of spectrogram stack and concatenated the 19 channels spectrogram to generate a single image. **Stage 2:** Load the pretrained networks and replace the final three layers for 8-class classification. **Stage 3:** Train the network using spectrogram data (70%) and test with the remaining data (30%).

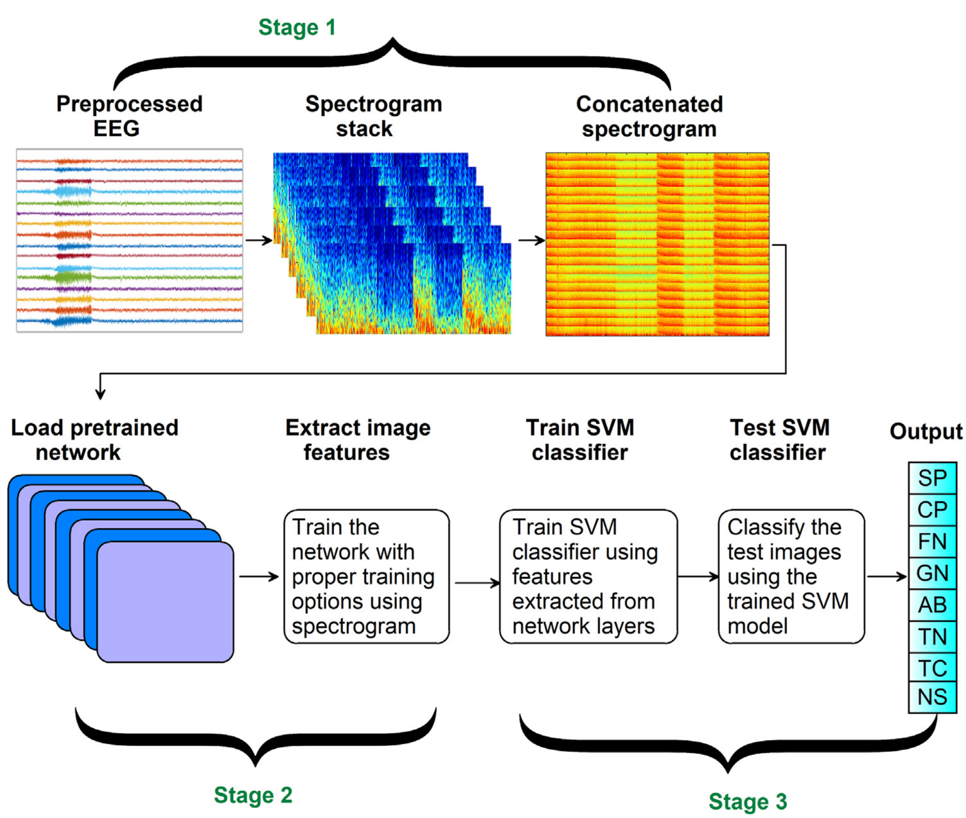

Fig. 2. Flow of the multi-class seizure type classification based on extract image features using pretrained network. **Stage 1:** Generation of spectrogram stack and concatenated the 19 channel spectrogram to generate a single image. **Stage 2:** Load the pretrained networks and extract the image features from specified layers. **Stage 3:** Train the SVM classifier using features extracted from layers and test the SVM model using the features extracted from the test images.

Table 2
Different pretrained networks used for the study.

Pretrained network	Depth	Number of layers	Image input size	Final three layers replaced
Alexnet	8	25	227 × 227	fc8, prob, output
Vgg16	16	41	224 × 224	fc8, prob, output
Vgg19	19	47	224 × 224	fc8, prob, output
Squeezenet	18	68	227 × 227	pool10, prob, ClassificationLayer_predictions
Googlenet	22	144	224 × 224	loss3-classifier, prob, output
Inceptionv3	48	316	299 × 299	predictions, predictions_softmax, ClassificationLayer_predictions
Densenet201	201	709	224 × 224	fc1000, fc1000_softmax, ClassificationLayer_fc1000
Resnet18	18	72	224 × 224	fc1000, prob, ClassificationLayer_predictions
Resnet50	50	177	224 × 224	fc1000, fc1000_softmax, ClassificationLayer_fc1000
Resnet101	101	347	224 × 224	fc1000, prob, ClassificationLayer_predictions

with LR of 1e-3 achieved the highest accuracy of 71.28%, 70.21%, and 68.21% using sgdm, rmsprop, and adam solvers respectively. Densenet201 network with LR of 1e-4 using adam solver showed the highest accuracy of 75.53%. For Resnet50 and Resnet101, LR of 1e-3 outperformed other LR's using all the three solvers and Resnet18 using rmsprop and LR of 77.66% showed the highest accuracy. Overall, LR of 1e-4 performed better in most of the solvers and pretrained networks. Finally, Googlenet showed the highest accuracy of 82.85% using LR of 1e-4 and adam solver.

Fig. 4 shows the predictions and their probabilities in descending order obtained using Googlenet. As it can be seen, TN and TC seizure type prediction probabilities are high as compared to other types prediction. Fig. 5 depicts the validation images with predicted labels and predicted probabilities using Googlenet. Predicted probability shows how well probability of an event (seizure type) is calculated from available data. The seizure types AB, FN, GN, CP, and SP showed the prediction probabilities greater than 80%.

Fig. 6 depicts the classification accuracy obtained using the extract image features approach. The image features were extracted from every layer and classified using the SVM classifier. As it can be observed, the classification accuracy gets improved in deeper layers of the pretrained networks due to higher-level features. However, the performance of the Densenet201 (refer to Fig. 6g) started fluctuating in deeper layer features. In contrary, Squeezenet and Googlenet (refer to Fig. 6d & e) did not show better performance in earlier layers. The remaining pretrained networks were capable of maintaining the less fluctuating accuracy in deeper layers features. The highest classification accuracy of 76.60%, 83.83%, 81.82%, 85.11%, 74.47%, 88.30%, 85.11%, 86.17%, 86.17%, and 87.23% was achieved using features extracted from Alexnet (layers 13–16), Vgg16 (layers 32 and 34), Vgg19 (layer 39), Squeezenet (layer 59), Googlenet (layer 56), Inceptionv3 (layers 37, 41, and 58), Densenet201 (layer 236), Resnet18 (layers 30 and 31), Resnet50 (layer 56), and Resnet101 (layers 101, 102, 105) networks respectively. Table 3 shows the highest classification accuracy obtained using the extract image features approach. Overall, ReLU layer showed the highest accuracy in most of the pretrained networks as compared to other layers. Finally, the highest classification accuracy of 82.85% (Googlenet using LR of 1e-4 and adam solver) and 88.30% (Inceptionv3 in layers 37, 41, and 58) was achieved using transfer learning and extract image features approach respectively.

4. Discussion

In this study, CNN was implemented successfully using scalp EEG for automated multi-class seizure type classification. The study was conducted using transfer learning and extract image features approach using ten pretrained networks. Both the approaches performed better for 8-class classification problem. We have performed a comparison between both the methods to identify the ideal model for seizure type classification. The best results from each pretrained network were taken into consideration for comparison. The best accuracy (using different solver and LR) of 77.66%, 69.15%, 65.96%, 69.15%, 82.85%, 71.28%, 75.53%, 77.66%, 72.34%, and 69.15% using Alexnet, Vgg16, Vgg19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 pretrained networks respectively was taken into consideration for transfer learning approach. Similarly, the highest classification accuracy of 76.60%, 83.83%, 81.82%, 85.11%, 74.47%, 88.30%, 85.11%, 86.17%, 86.17%, and 87.23% using Alexnet, Vgg16, Vgg19, Squeezenet, Googlenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 pretrained networks respectively were considered for extract image features approach. Fig. 7 shows the performance comparison between the results of transfer learning and extract image features using the pretrained network approach. Only for Alexnet and Googlenet, transfer learning approach outperformed image features approach. Further, an accuracy obtained using extract image features for Vgg16, Vgg19, Squeezenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 pretrained models outperformed transfer learning approach.

Fig. 8 reports the comparison between different LR's in terms of number of epochs, numbers iterations, computation time and classification accuracy among all three solvers. We observe that the LR of 1e-3 exhibits less number of epochs and iterations with less computation time and contrary to the results obtained using LR of 1e-6. A similar observation was made for all the three solvers: sgdm, rmsprop, and adam. Further, the highest classification accuracy was obtained for LR of 1e-4 using all the three solvers. We found that all ten pretrained networks showed similar observation.

Fig. 9 shows the comparison between the computation of taken for transfer learning and extract image features approach for each pretrained network in Matlab 2018a with a single GPU. Inceptionv3 has taken the highest computation time using both approaches. It is clear from Fig. 9 that the computation time required for extract image feature is high compared to the transfer learning method. This is because in extract image feature approach the SVM classification runs as many times of number

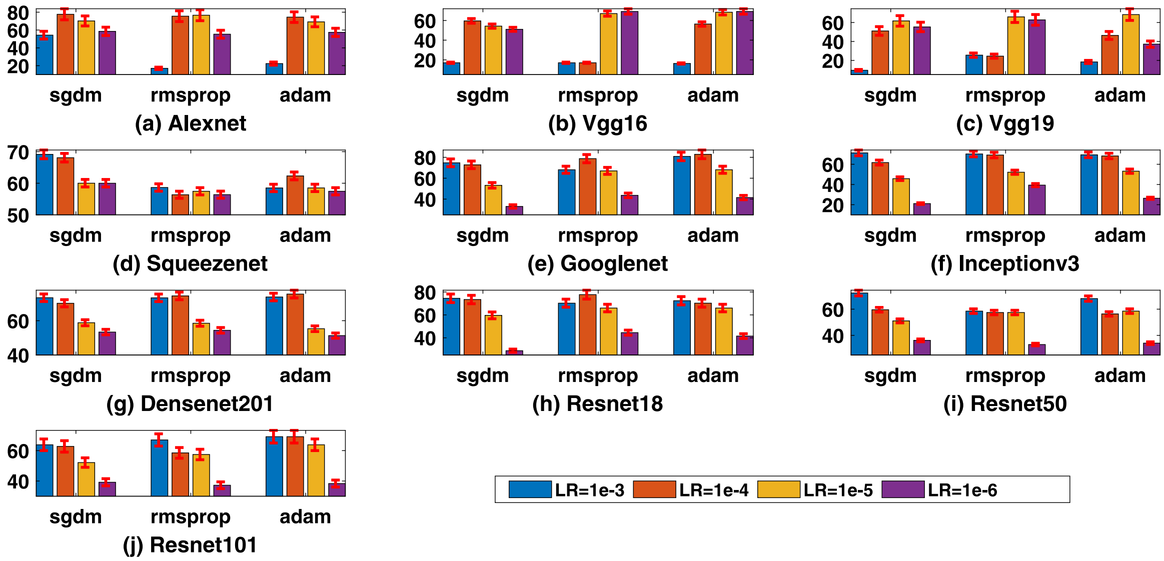

Fig. 3. Classification accuracy obtained for transfer learning using pretrained network approach. The results are grouped solver wise for each pretrained network.

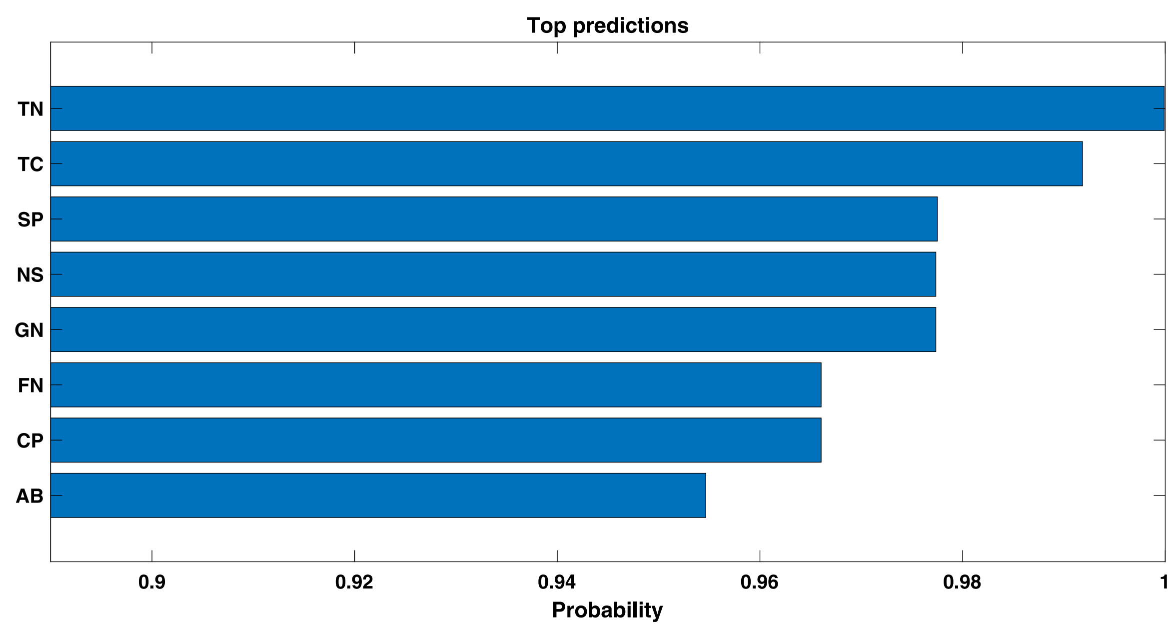

Fig. 4. Seizure type predictions and their probabilities obtained using Googlenet. SP-Simple partial seizure, CP-Complex partial seizure, FN-Focal non-specific seizure, GN-Generalized non-specific seizure, AB-Absence seizure, TN-Tonic seizure, TC-Tonic–clonic seizure, and NS-Non-seizure.

Table 3
The highest classification accuracy obtained for extract image features using the pretrained network approach.

Pretrained network	Highest accuracy (%)	Layer number	Layer name
Alexnet	76.76	13–16	ReLU, Conv, ReLU, and Pool
Vgg16	83.33	32, 34	Pool and ReLU
Vgg19	81.82	39	fc
Squeezenet	85.11	59	ReLU
Googlenet	74.47	56	ReLU
Inceptionv3	88.30	37, 41, 58	Normalization, ReLU, and Normalization
Densenet201	85.11	236	ReLU
Resnet18	86.17	30, 31	Conv, and normalization
Resnet50	86.17	56	Conv
Resnet101	86.27	101, 102, 105	ReLU, Conv, and Conv

of layers in the pretrained network. If we fix the best layer (refer to Table 3) with respect to the highest classification accuracy, the computation times gradually come below the transfer learning approach. In case of inceptionv3 in layer 37, the computation time required was 3.6 min which is lesser to transfer leaning approach (52 min) of same the pretrained network.

In order to compare the CNN based approach, we have applied two more methods namely (1) Standard multilayer perceptron

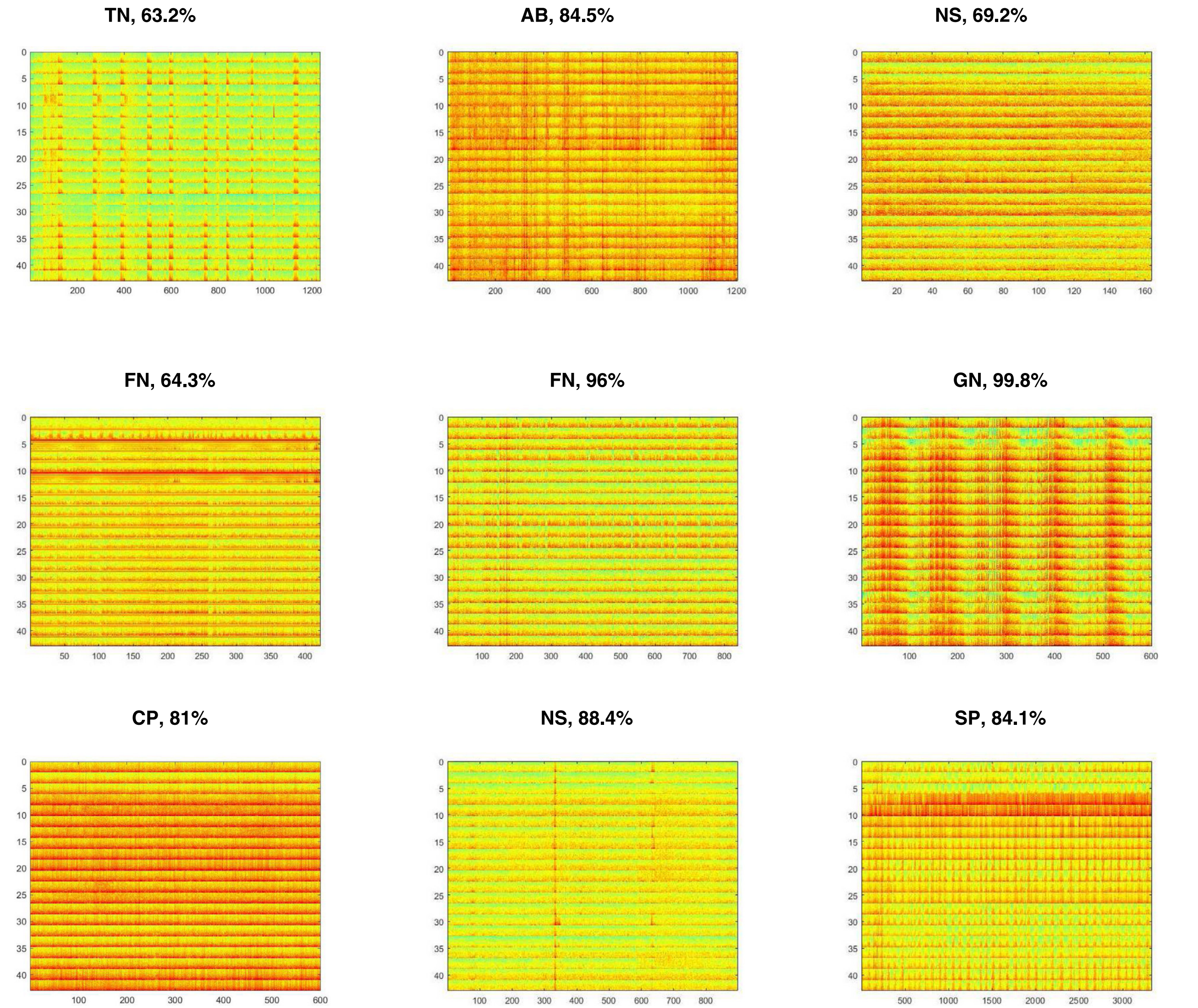

Fig. 5. Validation images with predicted labels and predicted probabilities using Googlenet. The text written on top of the images are predicted labels and predicted probabilities. SP-Simple partial seizure, CP-Complex partial seizure, FN-Focal non-specific seizure, GN-Generalized non-specific seizure, AB-Absence seizure, TN-Tonic seizure, and NS-Non seizure.

neural network (MLP-NN) approach and (2) Clustering approach. In the first method, we have applied discrete wavelet transform (DWT) using Haar wavelet on EEG signals till 5th level and extracted various features as reported in Chen, Wan, and Bao (2017), Lima and Coelho (2011), Lima, Coelho, and Chagas (2009) and Ubeyli (2009). The extracted DWT based features were classified using optimal MLP-NN as reported in Raghu and Sriraam (2017). MLP-NN was trained with following configurations: 10 hidden neurons, two-layer feed-forward, tan-sigmoid at hidden layer, pure linear at output layer, Levenberg–Marquardt as training function, maximum epochs of 1000, learning rate of 0.01, and cross-entropy as cost function (Raghu & Sriraam, 2017). The highest classification accuracy of 58.60% was obtained using the features extracted from 4th level DWT coefficients. Further, the same features showed the highest classification accuracy of 60.63% using the SVM classifier using radial basis function (RBF) kernel. In SVM classifier, hyper-parameter of RBF kernel was selected from the best parameters of sigma and box using Bayesian optimization method. In the second method, we have applied k-means clustering using city block distance metric for the same DWT based features as reported in El-Menshawy, Benharref, and Serhani (2015) and Orhan, Hekim, and Ozer (2011). From the silhouette plot, we observed few silhouette values were between −0.4 and 0.2 indicating that those clusters are not well separated (those are belong to seizure types). The accuracy was evaluated using results of clustering method and results with an expert's label. The classification results showed the highest classification accuracy of 64.20% using k-means clustering method. Therefore, it shows that CNN based supervised learning approach is well suited than MLP-NN and clustering approach for the proposed 8-class classification problem.

Since this is the first of its kind study of automated classification of multi-class seizure type, exact comparison cannot be made. However, a recent study by Roy et al. (2019) showed an F1 score of 0.907 using machine learning for 7-class seizure type classification. But, our study performed 8-class classification which is better than reported in Roy et al. (2019). Using the TUH database, a minimum variance modified fuzzy entropy obtained a sensitivity of 94.0% for classification of normal and epileptic seizures. Similarly, in our previous study (Raghu, Sriraam, Rao, Hegde, & Kubben, 2019), successive decomposition index using the SVM classifier showed a sensitivity of 95.80% using the same database. Further, many state-of-the-art methods have proposed a classification of normal vs seizures, non-seizure vs

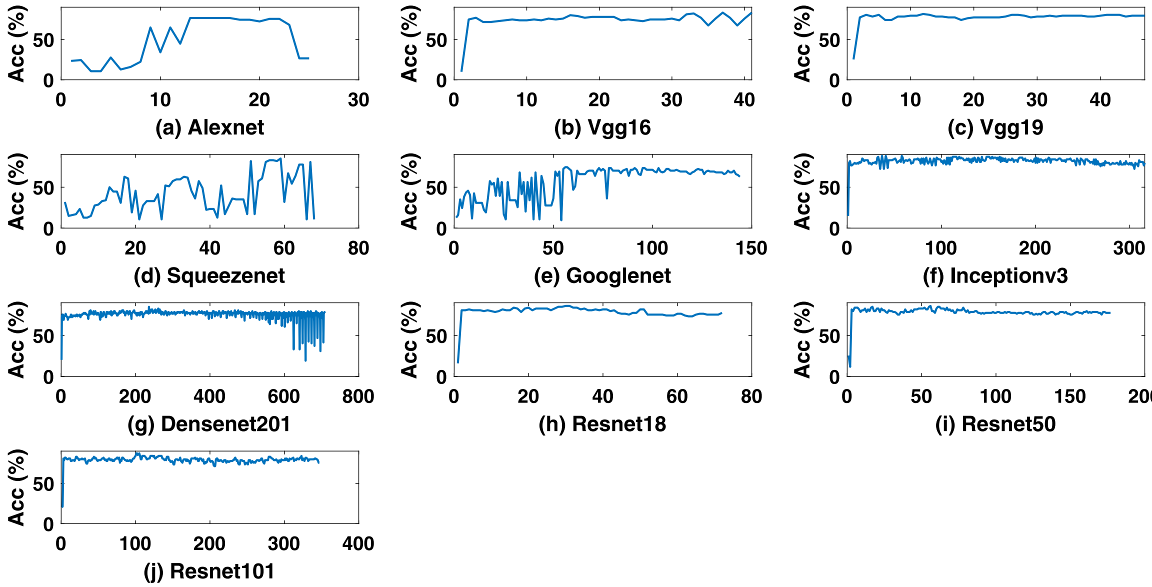

Fig. 6. Classification accuracy obtained for extract image features approach. The accuracy was plotted for each layer (along x-axis) for each pretrained network.

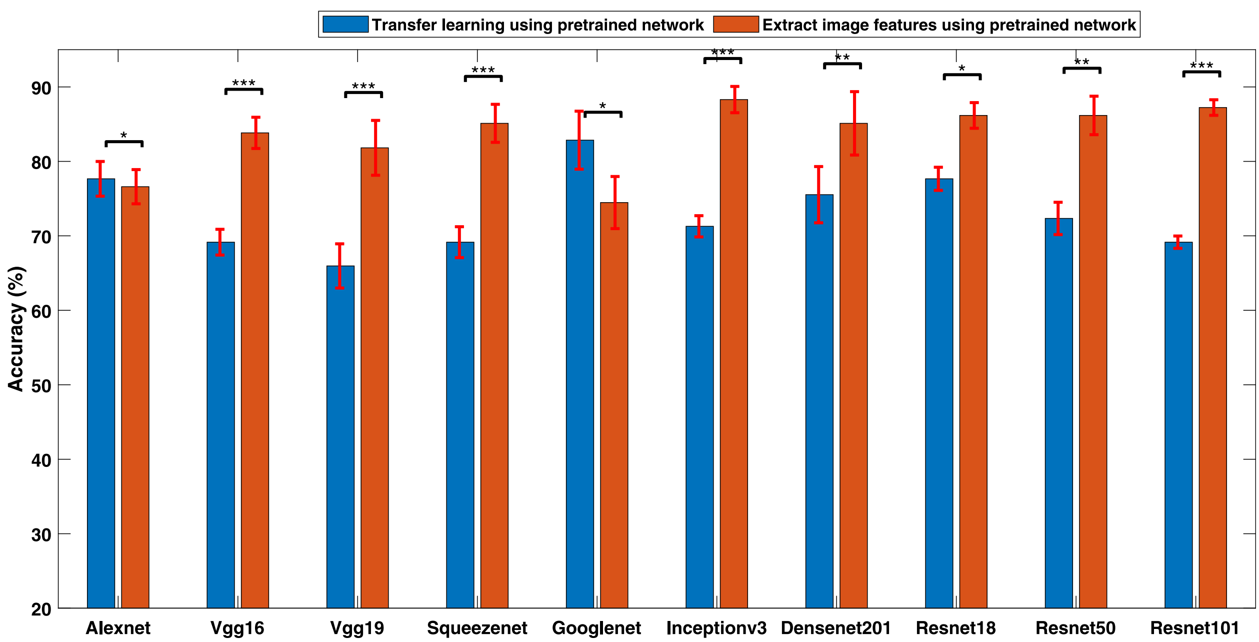

Fig. 7. Performance comparison between Transfer learning and extract image features approach using pretrained network. The highest results obtained in each pretrained network was considered for comparison. $p < 0.05(*)$, $p < 0.01(**)$, $p < 0.001(***)$.

seizure, inter-ictal vs seizure, and pre-ictal vs ictal using various EEG databases but not provided the automated algorithm for classification of multi-class seizure type (Acharya, et al., 2012; Acharya, Sree, Alvin, & Suri, 2012; Bogaarts, Gommer, Hilkman, van Kranen-Mastenbroek, & Reulen, 2016; Geng, Zhou, Zhang, & Geng, 2016; Raghu, Sriraam, Hegde, et al., 2019; Raghu et al., 2016; Raghu, Sriraam, Rao, et al., 2019; Srinivasan et al., 2007).

The major contributions and significant findings of the proposed study are listed below:

1. Generating the spectrogram stack using multichannel EEG to feed as input for CNN.
2. In order to overcome the imbalance issue of CNN, we have generated balanced dataset using overlap technique.
3. Using a transfer learning approach, LR with 1e-4 performed better in most of the solvers and pretrained networks.
4. The classification accuracy gets improved in deeper layers of the pretrained networks due to higher-level features learned by CNN using extract image features approach. However, the performance of the Densenet201 started fluctuating in deeper layer features.
5. ReLU and Conv layers (refer to Table 3) showed the highest accuracy in most of the pretrained networks as compared to other layer using extract image feature approach.
6. ReLU layer does not saturate and gradient is always high due to its property. Conv layer have filters to extract edges, shapes, textures, and objects of an image (spectrogram). Therefore, these two layers have shown the highest classification accuracy using most of the pretrained networks.

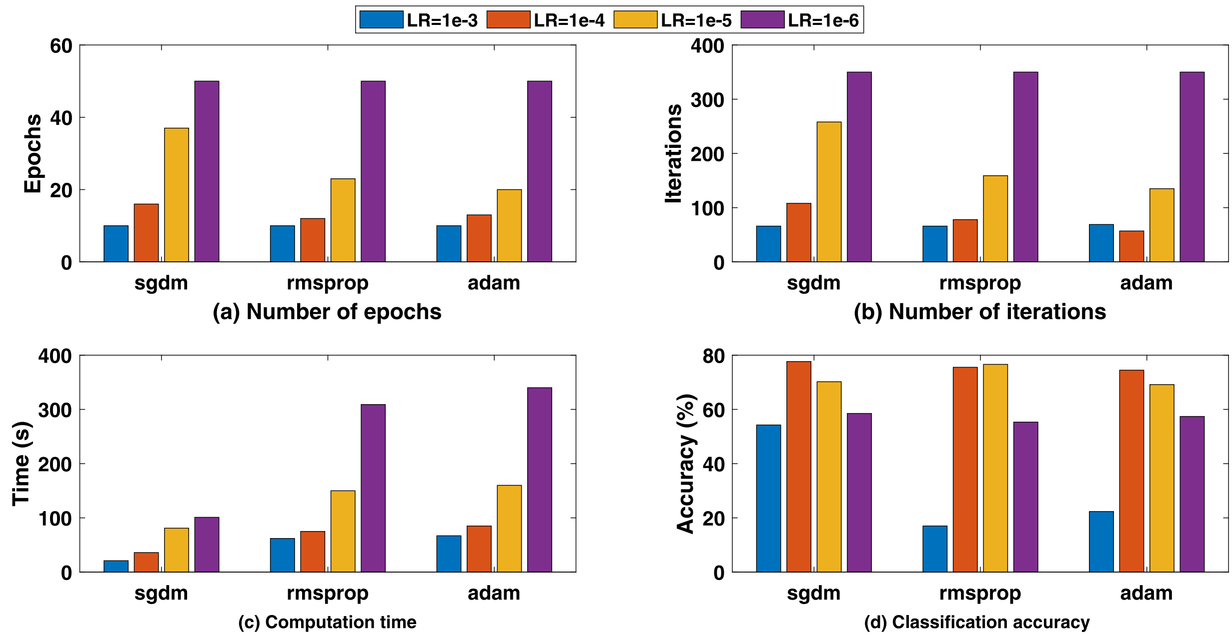

Fig. 8. The comparison between different LR's in terms of number of epochs, numbers iterations, computation time and classification accuracy. The number of epochs, iterations and computation time increases as the LR becomes smaller.

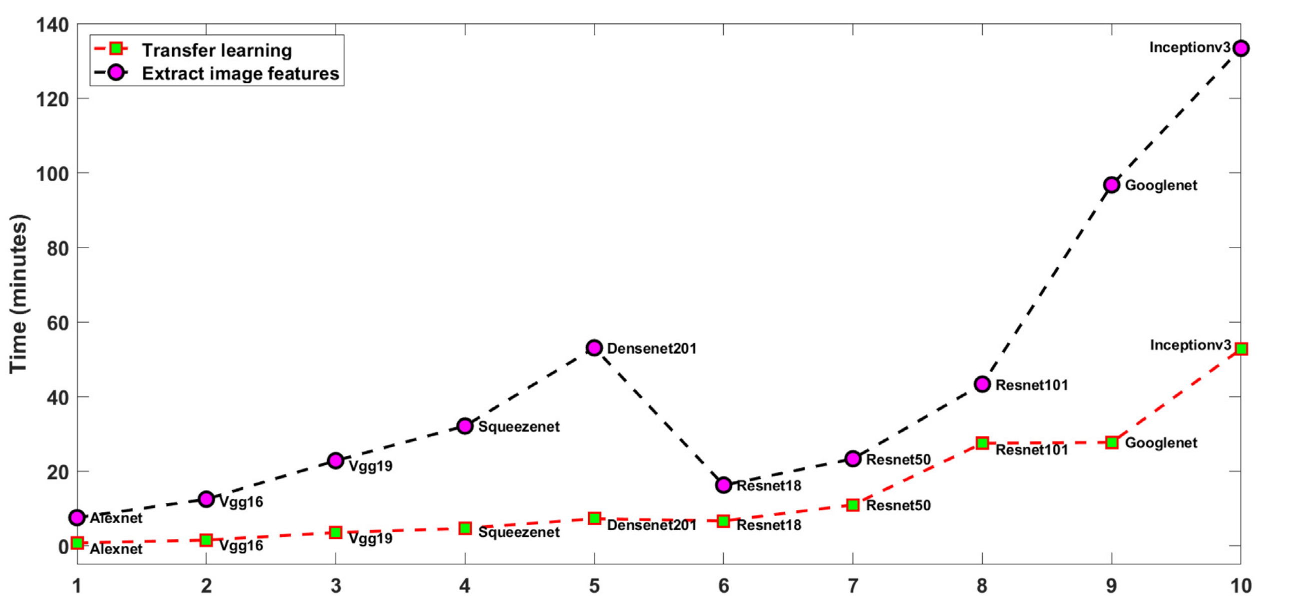

Fig. 9. Comparison between the computation time taken for transfer learning and extract image features approach for each pretrained network. The computation time given for extract image features approach is the cumulative time for all the layers of pretrained network used for the SVM classification.

7. Transfer learning approach using Alexnet and Googlenet outperformed extract image features approach.
8. Alexnet, Squeezenet and Googlenet did not show better performance in earlier layers using extract image features approach.
9. An accuracy obtained using extract image features for Vgg16, Vgg19, Squeezenet, Inceptionv3, Densenet201, Resnet18, Resnet50, and Resnet101 pretrained models outperformed transfer learning approach.
10. The highest classification accuracy of 82.85% (Googlenet using LR of 1e-4 and adam solver) and 88.30% (Inceptionv3 in layers 37, 41, and 58) was achieved using transfer learning and extract image features approach respectively.
11. Extract image features approach outperformed transfer learning approach in terms of classification accuracy and computation time.

The proposed study was conducted on MATLAB 2018a with Intel core i7 CPU@2.20 GHz and a single GPU. As a future scope, the obtained best model will be explored to enhance the classification results. Further, long short-term memory based deep learning approach will be introduced for classification of seizure types.

5. Conclusion

This study proposed an 8-class classification problem to classify seizure type using CNN. The EEG time series were converted into a spectrogram stack to feed as input for CNN. The algorithm was evaluated using transfer learning and extract image features using the ten pretrained networks. The proposed method showed the highest classification accuracy of 82.85% (Googlenet using LR of 1e-4 and adam solver) and 88.30% (Inceptionv3 in layers 37, 41, and 58) using transfer learning and extract image features approach respectively. Comparison results showed that extract image features approach outperformed transfer learning approach in terms of classification accuracy and computation time.

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