# Classification of Brainwaves Using Convolutional Neural Network

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***Abstract:*** **Classification of brainwaves in recordings is of considerable interest to neuroscience and medical communities. Classification techniques used presently depend on the extraction of low-level features from the recordings, which in turn affects the classification performance. To alleviate this problem, this paper proposes an end-to-end approach using Convolutional Neural Network (CNN) which has been shown to detect complex patterns in a signal by exploiting its spatiotemporal nature. The present study uses time and frequency axes for the classification using synthesized Local Field Potential (LFP) data. The results are analyzed and compared with the FFT technique. In all the results, the CNN outperforms the FFT by a significant margin especially when the noise level is high. This study also sheds light on certain signal characteristics affecting network performance.**

***Keywords*—Convolutional Neural Network (CNN), Brainwaves Classification, Fourier Transform, FFT, Deep Learning**

## I. INTRODUCTION

Interest in characterizing brainwaves has increased significantly among researchers in several disciplines in the past few decades. One reason for this is the need for improved analytics in a growing variety of applications ranging from detecting the onset of epilepsy/seizures and other signal characteristics, to the design of neuro-prosthetic brain-computer interface (BCI) devices[1][2]. For instance, engineers are using brain signals via BCI to control prosthetics and other medical aids for handicapped patients, and for those using insulin pumps. Another interesting analytics application used electroencephalography (EEG) patterns to recover visual information involved in face identification to reconstruct a facial image from neural signals related to a person's thought[3].

Brainwaves can be broadly classified into five categories based on their oscillation frequencies. They are thought to be associated with the different physical and emotional states of the subject[4]. For this reason, detecting the type of brain-wave prevalent temporally at particular sites is of great interest, and is being attempted now using multi-electrode configurations. The signals recorded typically have a poor signal-to-noise ratio (SNR) making it difficult for a linear method such as FFT to detect signal frequency reliably. Nonlinear techniques have been shown to be more successful in separating signals from noise. Popular non-linear techniques such as feed-forward neural networks require the extraction of features to operate effectively. So far, most of the effort has been focused on the development of methods for optimal feature extraction[5]. Various techniques such as Wavelet Transform, Power Spectral Density (PSD), Short Time Fourier Transform, autoregressive model, Principal Component Analysis have been applied to convert EEG information into low-level feature vectors which are then fed into off-the-shelf classifiers for classification. This has been a bottleneck in classification performance since most of these features are application-specific and are extracted under some assumptions which could introduce human bias. No matter how optimal the classification algorithm is, inadequate features could still lead to poor performance. That is the main reason that a good end-to-end model is required that can handle feature extraction and classification in a single framework.

One promising framework is the Convolutional Neural Network (CNN). It has been successfully used in many computer vision and image processing tasks such as face recognition, object recognition and tracking, and image segmentation. CNN has been applied to speech recognition[6], music classification, Time-series prediction, and classification[7], [8] with encouraging results. CNNs excel at finding complex features of spatiotemporal data which are resistant to partial deformation, rotation or translation. This attribute makes it a perfect candidate to model data with poor SNR. CNNs also have another important trait of parameter sharing that reduces the total number of unknown parameters.

This study makes use of the CNN based on the simple yet effective architecture developed by Oxford's renowned Visual Geometry Group (VGG)[9] for the classification of brainwaves. The network relies on both the time and frequency domains to extract complex pattern for classification, making it more robust for noisy input. We performed our experiments using a synthesizing dataset with different noise levels to study how noise affects the performance of CNN for our application. The CNN results are compared with those from the traditional FFT method since this is often used in the brainwave classification[10]. As the noise level increases the CNN outperforms the FFT in classification performance.

The main contributions of the paper include,

1) Designing a suitable CNN and investigating its performance in the classification of brainwaves in simulated Local Field Potential (LFP) recordings.
2) Gaining insights and characterizing the effect of noise on the CNN performance.
3) Illustrating the advantages of the non-linear CNN approach over the linear FFT method in classification performance and in contrasting their features.

## II. LOCAL FIELD POTENTIAL CHARACTERISTICS

Brain activity consists of a mixture of an oscillatory and non-oscillatory pattern. The oscillatory pattern has been hypothesized to indicate neural communication and information processing, whereas non-oscillatory activity was believed to be a spontaneous brain activity as a result of data collection techniques. However, recent studies have found its relation in uncovering brain functions such as consciousness and learning. This non-oscillatory activity exhibits a 1/f-like power spectrum and hence is described as 1/f electrophysiological noise[11][12].

There are various methods to record brainwaves. While EEG, which is recorded from the surface of the scalp is the most popular one, invasive methods including Electrocorticography (ECoG) and LFP provide more spatial and temporal resolution for brainwaves. In ECoG, the grid of electrodes is implanted on the exposed surface of the cerebral cortex of the brain to achieve a higher spatial and temporal resolution than EEG. To further improve the spatial and temporal resolution of the brainwave pattern and to get insights on the neuronal activity at deeper locations, metal or glass micro-electrodes or silicon probes are inserted within the cortical tissue or other deep brain structures. The signal obtained is then low-pass filtered (<250 Hz) to get the LFP pattern. Brainwaves are characterized by frequency (the rate at which neurons fire at the same time), amplitude (how many neurons fires at the same time) and phase. Depending on the oscillation frequency the brainwaves, they are broadly categorized as 'Delta'(0.5-4 Hz), 'Theta'(4-8 Hz), 'Alpha'(8-12 Hz), 'Beta'(12-30 Hz) and 'Gamma'(30-80 Hz)[13].

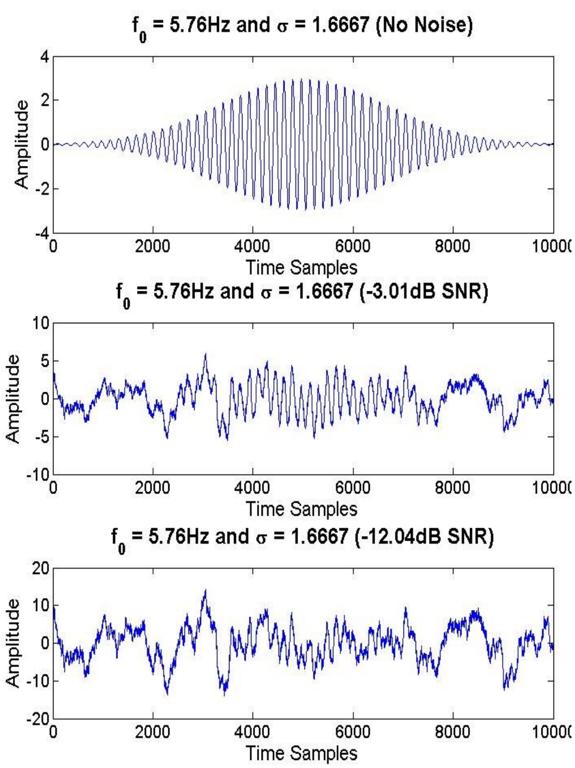


Fig. 1 Brainwave burst examples: without noise (top), with noise at -3.01 dB SNR (middle), with noise at -12.04dB SNR (bottom).

The improved resolution of LFP recordings (compared to scalp recordings) can be very useful in more precise detection of neural activity. A single wave burst can be mathematically modeled as

$$x(t)=A(t)\cos(\omega_0+\phi)+ n(t),\ -T\leq t \leq T \tag{1}$$

where, the Burst envelope A(t) can be modeled by a Gaussian

$$A(t)=A_0 \exp\left(\frac{-1}{2\sigma^2}\ t^2\right) \tag{2}$$

with $\sigma^2$ controlling the burst width, and
$\omega_0$ = brainwave angular frequency
$\phi$ = random phase
$n(t)$ = pink noise whose PSD follows the 1/f characteristic mimicking 1/f electrophysiological noise.
Fig. 1 shows a few LFP brainwave bursts for different noise levels.

## III. METHODOLOGY

A CNN is a concatenation of many units and each unit is composed of the 3 layers, a convolutional layer, a max-pooling layer, and an activation layer. The convolutional layer applies a set of filters to an input that processes a small local region at a time. This is based on the fact that the feature learned at a certain part of the input can be applied to the entire input space. A max-pooling layer performs progressive downsampling of the spatial size of feature maps created by the convolutional layer to reduce the number of parameters and computation, and hence avoids overfitting. It does so by taking the highest of feature map activations within a specified window (usually 2×2). It aids in making CNN robust to shifts and distortions in the input. An activation layer breaks the linearity in the network created by a convolutional layer. A stack of these layers reduces an input into a set of self-learned complex feature vector which is used by a set of fully connected layers for classification[14].

### *A. Network Architecture*

The Deep Convolutional Neural network used in this study is based on the VGG architecture[8]. Although it has the disadvantages of longer training time and requiring considerable processing power, its design simplicity and superior classification performance makes it appealing for our application. VGG creates a simple model by stacking a series of convolutional layers with small receptive field. It manages to achieve the performance of a model having a larger receptive field with a smaller number of parameters.

The network exploits the locality characteristics of a brainwave signal along time and frequency axes. A signal burst is passed through a filter bank of 16 different bandpass filters to introduce the frequency axis. The intuition behind this is that different brainwaves and additive noise have their energy concentrations in different frequency regions. The filters in the convolutional layers can efficiently represent these local structures and their combinations along the whole frequency axis, ensuring better network performance for

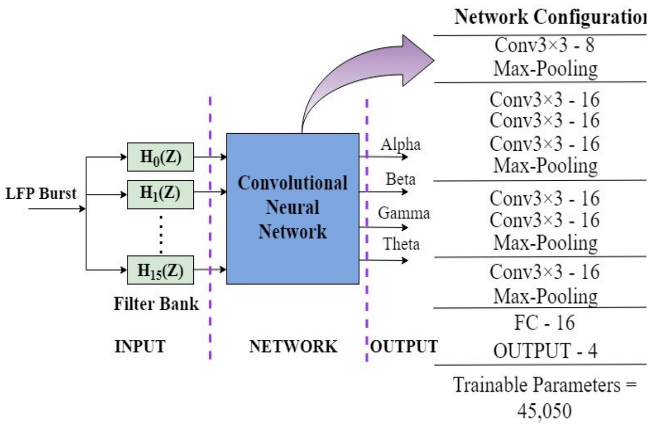


Fig. 2 Convolutional neural network structure and configuration with a total number of trainable parameters. The convolutional layer parameters are denoted as conv<receptive field size> - <number of filters in that layer>

noisy input. Each filter in the filter bank is an FIR filter with order 200; having a 5Hz bandwidth. The cut-off frequency of the last filter is 80Hz which covers the entire range of brainwave oscillation frequency. A 3×3 size filters were used in the convolutional layer throughout the network along with a 2×2 window and stride for max-pooling. Using Convolutional layers multiple time in sequence provides a larger receptive area for extracting complex features. However, as the spatial area of input decreases after each max-pooling layer, the larger receptive field doesn't provide additional useful information. As such the sequential use of the convolutional layer is progressively reduced in the higher layers of the network. Fig. 2 provides the structure and configuration of the proposed network.

### B. *Network Training*

The training is carried out by optimizing the cross-entropy loss function. Nesterov Adam (Nadam) optimizer with an adaptive learning rate has been used for faster training. The learning rate starts at $1\times10^{-3}$ and is reduced by half each time if there is no improvement in validation loss for 10 epochs. Exponential Linear Units (ELU) are applied as activations for all layers except for the output layer where SoftMax provides the classification. Schirrmeister R. *et al.*[15] found batch normalization can provide performance improvement in brainwave decoding accuracy. As such, batch normalization has been applied between each convolutional and activation layer to improve the training speed and performance. The network prevents overfitting by using an L2 penalty regularizer of value $1\times10^{-2}$ along with dropout. The dropout ratio is fixed at 0.2 in all convolutional layers and 0.5 for fully connected layers due to the higher number of trainable parameters. The training is done in small batches of 128 and is stopped after 100 epochs. After each epoch, the data is shuffled randomly to avoid any bias it may create for the optimization algorithm. Initialization of the network weights is important for the performance of such deep nets. As uniform He initialization (he_uniform) takes the non-linearity introduced by ELU into account, it is used in all layers with ELU as an activation function (all convolutional and first fully connected layer). The uniform Xavier initialization (glorot_uniform) is utilized for the output SoftMax layer.

## IV. EXPERIMENTS AND RESULTS

To gain insight and understanding for end-to-end classification of brainwaves using CNN, we synthesized a dataset that exhibits the characteristics of LFP with brainwaves embedded using (1). A long-time sequence of LFP data is formed at a sampling rate of 1KHz, with pink noise added at a certain SNR. An initial energy detector is applied to detect the temporal locations where brainwave bursts may appear. A segment of 2 seconds long around the detected temporal location is isolated, which is then passed through the filter bank to generate the input of CNN for classification. The data collection has 20,000 burst segments, containing 5000 bursts for each of the brainwave categories: 'Theta', 'Alpha', 'Beta' and 'Gamma'. The total dataset has three collections, one that does not have noise, another at moderate SNR -2.88dB and one more at lower SNR -11.93dB, resulting in a total of 60,000 bursts.

### A. *Results*

The training of a neural network depends on the randomness and quality of the training dataset. We used 5-fold cross-validation to test network performance, which was done separately for different SNRs. The average accuracy values of the 5-folds are shown in Fig. 3 along with FFT results for the three data collections. The FFT results are generated by $2^{18}$- point FFT with zero padding. FFT identifies the brainwave category by determining the frequency range at which the peak in the magnitude spectrum lies. It behaves well in no noise situation and it even has slightly better performance than CNN. As FFT is a linear operator, its performance could suffer in an extremely noisy environment. The limitation of FFT is apparent in Fig. 3 as noise level increases, where CNN outperforms FFT by at least 20% in classification accuracy at low SNR.

### B. *Analysis*

While it is not straightforward to determine the specific reasons for the superior performance of the convolutional

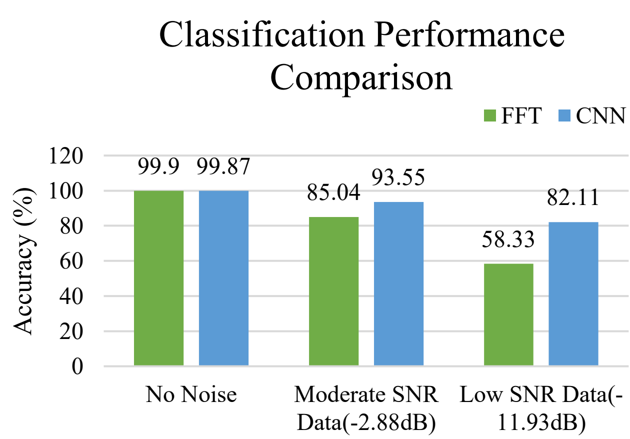


Fig. 3 Classification results at different SNRs by FFT and CNN. The CNN results shown are the mean accuracies of 5-fold cross-validation

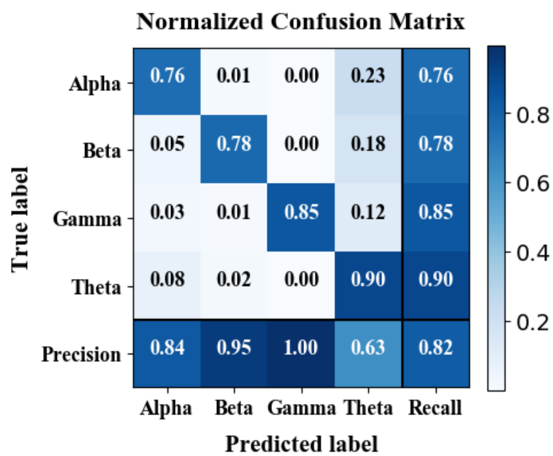


Fig. 4 Normalized confusion matrix for classification of low SNR data set by CNN

network, we can obtain some insight by examining its performance for the individual brainwave category. We have also used the ground truth information of each brainwave amplitude, the number of cycles and oscillation frequency to understand their effect on the CNN performance.

Figs. 4 and 5 lists the normalized confusion matrices of CNN and FFT for the classification of the low SNR data. As pink noise has higher energy in lower frequencies, other brainwave categories are misclassified often as Theta which has the lowest frequency region among the four. This is reflected in Fig. 4 where theta has the lowest precision and highest recall values. It means the CNN is predicting most of the brainwaves as Theta and also has the lowest detection error. In general, the category having lower frequency range has lower precision. Similarly, there is a correlation between the width of frequency region for the other categories (apart from Theta) and their recall values where lower frequency range has lower recall values. This is because a lower frequency range has a higher number of signals near the category boundary which leads to a higher chance of misclassification. These results are consistent with those from using FFT and can be observed in Fig.5 where more than 50% of the other categories signals are classified as Theta.

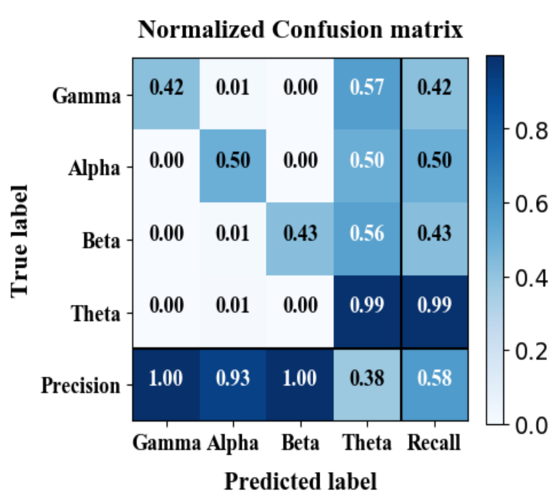


Fig. 5 Normalized confusion matrix for classification of low SNR data set by FFT

To scrutinize these results, Fig. 6 plots magnitude versus frequency of the misclassified brainwaves in the noiseless data set. The predicted categories are represented by different colors. Even with few misclassified signals, one can see a clear pattern where signals with their frequencies very close the category frequency boundary are misclassified, e.g., Theta waves are misclassified as Alpha. Another interesting pattern to notice is that most of these bursts have a lower amplitude. In the presence of noise, the issue of low amplitude brainwaves become more serious as such signals can be easily dominated by noise. So, as expected, a higher number of lower amplitude signals are misclassified as the noise increases. This is shown in Fig. 7(a), which represents a similar plot for the low SNR data set. Most of the signals that are misclassified due to low amplitude are predicted as Theta. This observation further supports the explanation for its lowest precision. In a similar plot for FFT in Fig. 7(b), no such patterns appear, and misclassification results are completely random to infer insights.

We have also experimented with a 1D convolutional network which is a classical use of time domain convolution to find a relation between adjacent time samples using temporal information. After separating a burst, it is directly fed to the network by omitting the filter bank step. We found that by adding such a step and changing the network from 1D to 2D, the classification performance can increase up to 3.85%. However, even without that performance boost, the 1D network provides a significant improvement over FFT as well with a 79.07% classification accuracy on the low SNR data set.

## V. CONCLUSION

The objective of this research is to study the possible improvement of brainwave classification through the use of CNN. This is achieved by creating the VGG architecture-

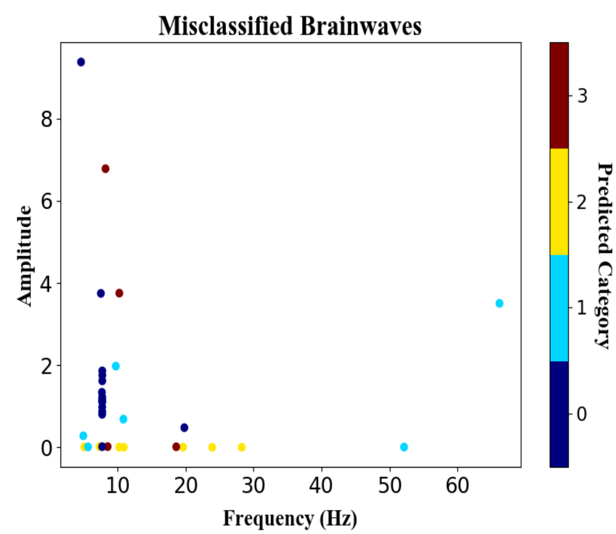


Fig. 6 Misclassified brainwaves plot for noiseless data by the CNN. Each dot represents a misclassified signal segment. The original category of the brainwave can be known from frequency axis while the predicted category is represented by color. 0: Alpha, 1: Beta, 2: Gamma, 3: Theta

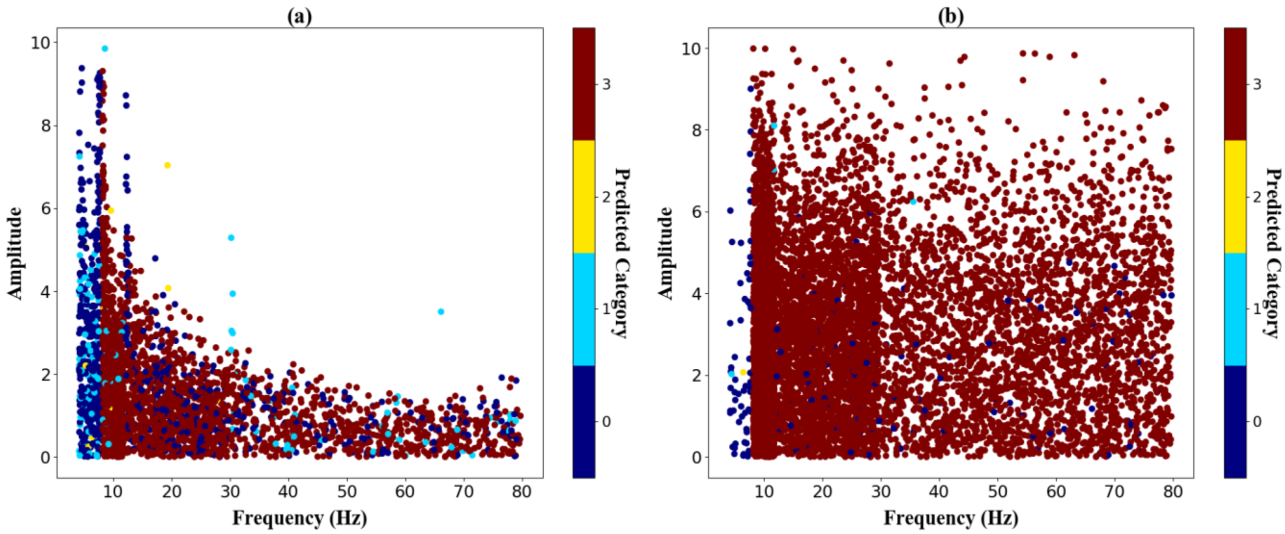


Fig. 7 Misclassified brainwaves plot for low SNR data set by (a) convolutional network and (b)FFT. Each dot represents a misclassified signal segment. The original category of the brainwave can be known from frequency axis while the predicted category is represented by color. 0:Alpha, 1:Beta, 2:Gamma, 3: Theta

based CNN that takes a filter bank output of a brainwave burst for classification. The purpose of the filter bank is to enhance performance in a noisy environment as the desired signal and noise can be located in different frequency regions. We have conducted our experiments using synthesized LFP brainwave signals that have better spatial and temporal resolution than EEG, where pink noise is added at several SNRs.

As the noise level increases, the proposed CNN has significant performance improvement over the FFT method. Analysis indicates that the misclassification of CNN comes from brainwave bursts having low amplitudes and frequencies in the vicinity that separates different brainwave categories. On the other hand, FFT showed no such pattern and its performance limitation is purely caused by its linear processing nature and the amount of noise in the signal. We anticipate that CNN will outperform FFT for other signal processing and classification problems as well. Future work will include the comparison of CNN performance with nonlinear filtering methods that can be more robust in low SNR conditions, such as Empirical Mode Decomposition along with standard machine learning techniques including random forests and multitask regression analysis.

The current study uses synthesized data for understanding and to gain insight. We plan to apply the proposed CNN to the actual LFP measurement for brainwave classification. Furthermore, we will examine the effect of varying segment burst lengths and of the pink noise characteristics on the CNN performance. We also plan to extend the study by considering it as a multilabel classification problem where the signal is the combination of overlapping alpha, beta, gamma and theta wave bursts having different frequencies and amplitudes.

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