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A Comparison of CNNs and LSTMs for EEG Signal Classification

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***Abstract*—Non-invasive EEG devices have shown novel applications from neuro-biological exploration to robotic control. Controlling robotic movements using brain activity requires accurate processing of real time multi-channel data for classification into multiple classes for actuating the robot. Multiple networks ranging from convolutional and recurrent neural networks have been used to classify the time-encoded analog data stream. In this work, we study the classification of a 14-channel EEG device using convolutional neural networks (CNN) and long-short term memory (LSTM) for wrist motor response classification. Varying network structures suggested that CNNs consistently outperformed LSTMs in accuracy by approximately 10%. In the second step, we evaluated the relative importance of the channels where a subset of the EEG channels were provided as inputs to the classifier and the results showed that the CNN performance dropped quicker with a reduced number of channels. We also identified a set of channels with the least effect on classification performance while comparing the individual contributions of the channels in the classification output. The results of this work may help in choosing network architectures and sensitive brain regions for future low power EEG applications.**

I. Introduction

Processing of electroencephalogram (EEG) signals from the brain finds wide variety of applications in rehabilitation [1], robotic control for walking robots [2], robotic arm [3], etc. The sampling of signals happens through multiple channels in the brain computer interfaces, which captures the local potential at points on the scalp to generate continuous waveforms. This multi-channel input then undergoes preprocessing to remove noisy fluctuations that then pass through a neural network for classification.

Neural signal generation corresponding to motor or cognitive tasks provides a simple classification paradigm to classify EEG output based on the motor action it corresponds to. Multiple motor actions such as the motion of limbs [4], blinking of eyes [5] etc. have been approached for classification using multiple processing backends ranging from CNNs, LSTMs [3], and even SNNs [6]. Dedicated networks have also been proposed for high-performance operations [7]. The relative advantages of these methods for such motor classification tasks are not fully clear [8].

In this work, we use CNNs and LSTMs for comparing a 4 output classification task. 3 layered networks with one hidden layer are constructed for both CNNs and LSTMs with varying numbers of filters for CNNs and varying numbers of hidden layers for LSTMs. The accuracy of classification and number of operations are compared for hardware implementation. Our results reveal that CNN provides betters accuracy but is more susceptible to the number of channels being used.

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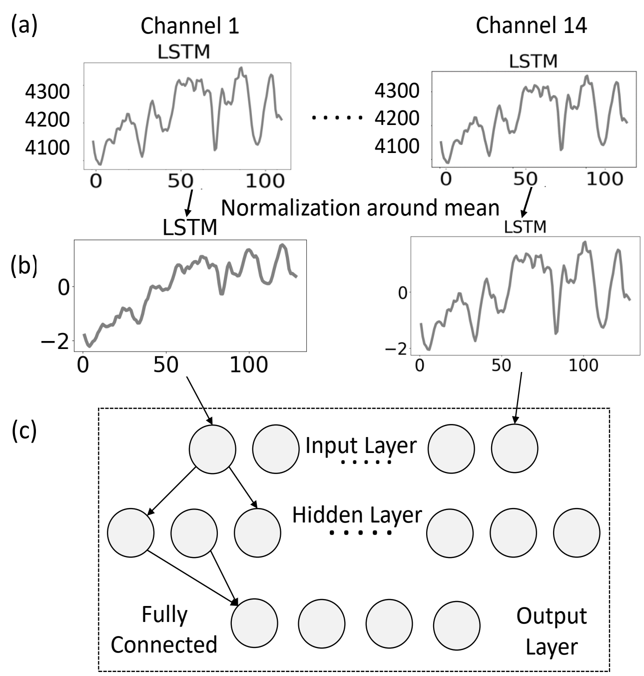

Fig. 1. (a) Original recorded data (b) data after normalization (c) Network structure for the classification task

II. Methodology

A. Data Acquisition

A fully charged device is connected to a laptop via Bluetooth USB dongle for the experiment. Electrode felts were soaked in a mild saline solution before application to the subject's head. The experiments took place in a quiet room, to limit noise in our recordings, e.g. auditory stimuli. Felts were placed into electrode sockets and the headset was positioned on the subject's head. The headset was adjusted until electrode contact quality (CQ) hit 100%. The subject was given around 5 minutes to relax. This was done to let EEG signal quality reach 100%. The subject was instructed to close their eyes to limit the influence of visual stimuli. Trials were timed for 5 minutes, of which the first and last 30 seconds would be removed. This was to avoid corruption in the waveforms while they were settling to stable values. The subject was asked to place their left wrist in the down position and hold the position for 5 minutes. The EEG headset was set to record data at a frequency of 128Hz. The recorded data was broken into 128 samples each as inputs to the classification network. At the end of the 5 minute window, the recording was stopped and the subject was asked to repeat the above steps for the left wrist up, right wrist down and right wrist up positions. Fig. 1 describes the procedure for data acquisition. Fig. 1(a) shows the acquired data through the channels for a single input to the classification network.

With the resulting data files, for each action, the mean of each channel was found and hence the standard deviation. This was used to screen files before adding them to our input data set. The output file for each action was split into multiple files each with a length of 128 samples. These files were named in ascending order by the order in which actions were performed. For each batch of 128 samples, the mean was found for each channel and the standard deviation from the mean of all the samples for that action was found. Any batch that exceeded 4 standard deviations was discarded. Only batches under 4 standard deviations were allowed to be added to the input data set. Furthermore, of the data samples that were allowed through our screening process, they were normalized about the mean to operate more efficiently with TensorFlow. The normalized inputs are shown in Fig. 1(b). The time-encoded input is passed through the network to generate an estimate for the hand position of the subject. The inputs are randomly selected corresponding to each one of the outputs to avoid biased classification. The data was then split where 80% was used as training data and 20% was used to test the model. The networks had varying numbers of parameters (for both the CNN and the LSTM) to compare the performance across the number of parameters.

B. LSTM

Long short-term memory forms a popular network choice for temporally continuous data where the dependence of the current sample on the previous samples is of importance. LSTM has been used previously in [9] for EEG classification. We use a network consisting of one input layer, an LSTM layer each followed by a "dropout" layer, a dense layer and a Soft-max/Activation layer. The network started with an input layer of 14 channels and 128 samples. The number of hidden units was varied to find an optimal point. The output is read out using a softmax activation layer for output classification. We also used categorical-cross-entropy and adam optimizer for training.

C. CNN

The majority of the deep learning applications used in EEG data classification use CNNs [9]. CNNs are applied on the fully recorded data with multiple filters capturing the temporal patterns within a channel and its interaction with the other channels. Our CNN consisted of a one-dimensional convolutional layer with a varying number of filters, followed by a pooling layer, dropout, and a fully connected output layer with a softmax activation function. The number of filters were varied in multiples of 12. The CNN used 80% of the data for training and 20% of the data for validation. The CNN was also trained using categorical-cross-entropy and an adam optimizer.

III. Results

A. Optimal Number of Hidden Layers

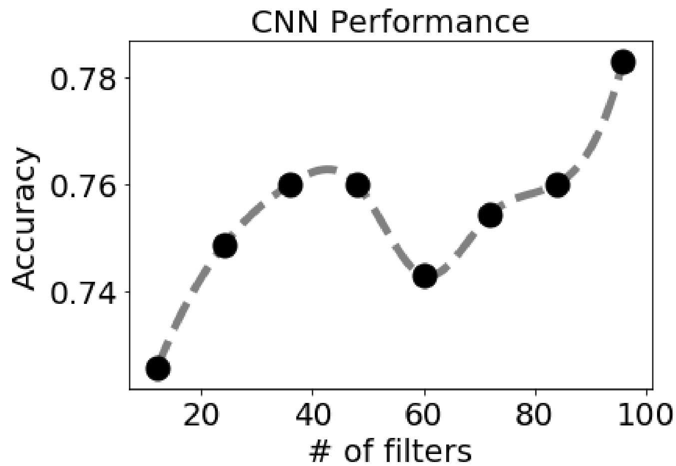

Fig. 2. The accuracy of the CNN on classifying the correct wrist position of the subject across different numbers of filters.

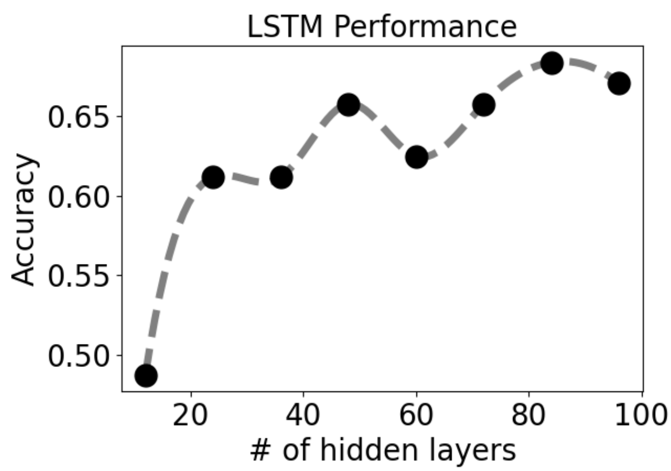

Fig. 3. The accuracy of the LSTM on classifying the correct wrist position of the subject across different numbers of filters.

We undertake 2 studies consisting of finding the optimal number of hidden layers and assessing the relative importance of the channels and thereby the active regions within the cortex. First, we varied the number of filters for the CNN and found validation accuracy for each number of filters. The results are shown in Fig. 2 where the network performance rises initially but then falls, possibly because of overfitting. A similar experiment was repeated with LSTMs, and the optimal number of hidden layers was found to be 84 as shown in Fig. 3. The network accuracy was observed to be consistently rising

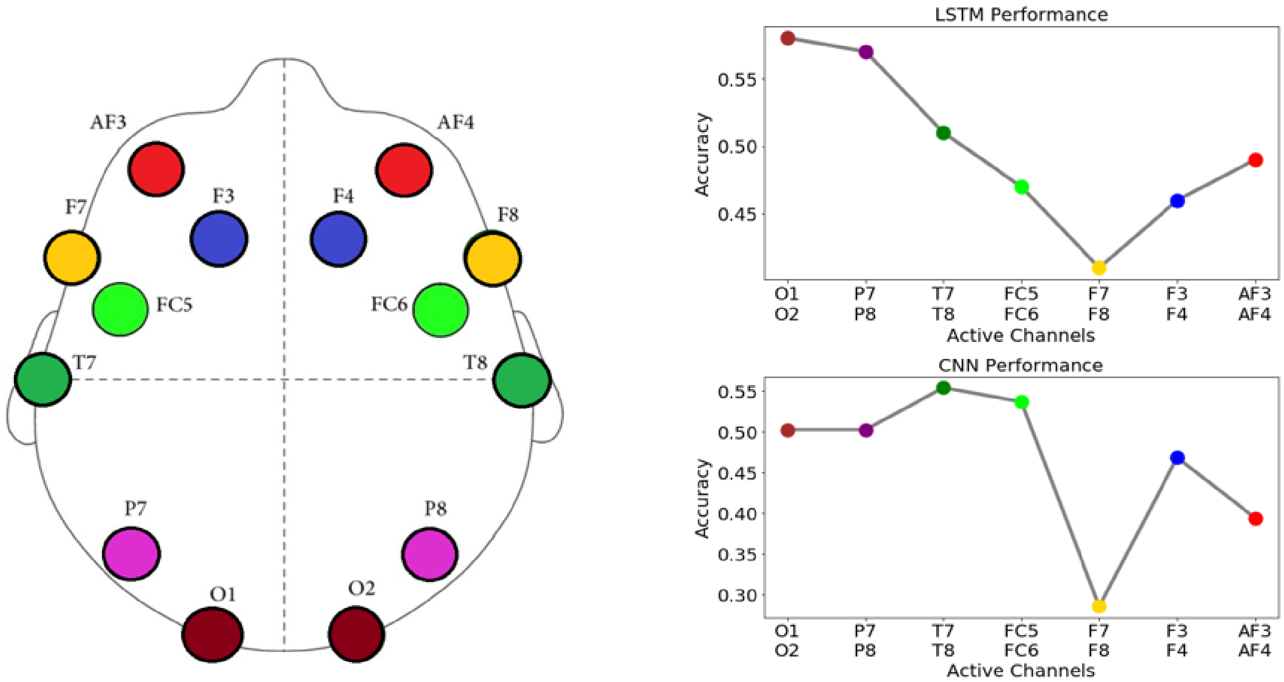

Fig. 4. Diagram comparing the performance of a CNN and LSTM when only using data from the indicated channels. The color of the channels on the head diagram to the left are correlated with the color of datapoints on the right. Channels around the motor cortex (T7/T8 and FC5/FC6) were expected to have a greater amount of useful information, but empirical results showed that channels at the back of the head were more consistently useful across the LSTM and CNN.

with additional numbers of hidden layers. It is important to note that the variation in LSTM performance is higher with the network structure whereas CNNs are mainly agnostic with additional filters. The accuracy is seen to be higher for the typical CNN, explaining their popularity.

B. Relative Importance of Channels

In the next step, both networks were reconfigured using their respective optimal hidden layers and were now run with only two channels from the EEG at a time as color-coded in Fig. 4. This is to check if motor tasks have a significant dependence upon a specific region on the head causing channels in a particular region to be of relatively higher importance. The CNN was implemented with 36 filters, and the LSTM was implemented with 84 hidden layers due to the results of the previous experiment. The two channels were also chosen to be on opposite hemispheres of the brain, and therefore should be important to run together as the brain hemispheres are thought to be roughly equivalent and will have similar behavior.

The results are shown in Fig. 4 (see Figure 4.). It was expected that areas near the motor cortex (approximately the electrodes FC5/FC6 and T7/T8 in Figure 4.) would be the most important, as the networks were classifying for motor data from the wrist. While the CNN did have relatively high performance on the FC5/FC6 and T7/T8 channels, these results were not supported in the LSTM. In fact, it was the O1/O2 and P7/P6 channels that were most consistently higher performing across both the LSTM and CNN, which are located at the back of the head. F7/F8 was consistently the worst performer across both the LSTM and CNN. The accuracy for CNNs drops significantly from moving to 2 channels from 14 whereas the drop is relatively smaller for LSTMs. This shows that the CNNs capture the overall relative activity within the channels more accurately and rely on the inter-channel interactions more than LSTMs.

IV. Discussion

This project had issues with noise during data gathering. The EEG was very sensitive to very small disturbances in noise, and the disturbances could not be completely removed within a quiet lab setting. The data also differed depending on the mental state of the subject and required the subject to be almost completely still, as the EEG was much more sensitive to muscular disturbances than to brain signals. However, the noise and lack of precision and accuracy from the headset is not a complete negative, as our results show that even in noisy environments with a noisy EEG the algorithms can still produce results.

We observe that CNNs consistently demonstrated higher accuracy compared to the LSTMs while using the data from all channels. However, the accuracy was lower for CNNs when inter-channel interactions could not be considered while using only two channel inputs. The consistent low importance of the F7 and F8 channels may be of interest to the neuro-engineering community.

V. Conclusion

We studied the classification of EEG data using CNN and LSTMs for a commercial 14-channel EEG device. CNNs generally show higher accuracy for classification with different numbers of hidden units. However, its performance is more susceptible when limited to a number of input channels.

Comparing the other common networks for benchmarking the performance of different network topologies may be of interest for edge-processing community when the network is to be implemented near the BCI device.

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