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An Experimental Analysis of Various Deep Learning Architectures for the Classification of Cognitive Stimuli based EEG Signals

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***Abstract*— The human brain functions through electrical signals. By measuring these signals, one can monitor brain activity and gain insights into the brain function of the subject. An electroencephalogram (EEG) allows one to monitor brain activity by having the subject wear an array of sensors on their head. This process is frequently used to diagnose medical conditions such as epilepsy.**
In recent years, there have been efforts to use EEG signals in concert with deep learning to create a brain computer interface (BCI). Such a device would enable the wearer to communicate to a system via brain signals. While such a system would not be so advanced as to enable the translation of complex thoughts, it would enable a user to command a machine to perform a small number of functions.
The objective of this paper was to develop and optimize recurrent neural network architectures for use with a brain computer interface. Using EEG data collected from subjects, a variety of neural network models were created to learn from the data. The models that were used were simple recurrent neural networks (RNN), long short-term memory (LSTM), and gated recurrent units (GRU). This paper proposes a novel approach to EEG signal classification, demonstrating the capabilities of recurrent networks which are seldom explored for this purpose.
This study produced promising results for recurrent models, obtaining a 91% accuracy with the 4-layer LSTM architecture. This presents a solid foundation for the argument that LSTM and similar architectures are feasible for BCI applications.

***Index Terms*— Deep Learning, Recurrent Neural Networks, Long Short-term Memory, Gated Recurrent Unit, EEG, Brain Computer Interface**

I. Introduction

A Brain Computer Interface, just like any other interface, is a means by which to communicate with a computer. All computer interfaces provide a medium by which a human being or other external entity can communicate and interact with the computer. In the case of a Brain Computer Interface, the medium of communication is brain signals.
The human brain functions through electrical signals passed from neuron to neuron. These signals can be measured from outside the brain using an electroencephalogram (EEG). An EEG measures brain signals using small metal discs attached to the scalp. As the brain sends signals from neuron to neuron, the electric potential can be sensed

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outside the brain. These potentials can be measured in specific areas of the skull, each representing function in a different area of the brain. EEG signals can provide valuable information about the processes occurring in the brain.

The goal of a BCI is to interpret these signals to enable communication with a computer. In essence, this means that the user would be able to use just their thoughts to control the computer. The primary obstacle to developing a BCI is that every brain is unique. Therefore, the EEG signals produced by each person is different. In order to create an effective BCI, it would need to be bespoke. A BCI must be able to understand the signals of the user, and must therefore be trained to understand the unique signals of the brain that it is designed to interface with. There are a few promising ways of achieving this, but perhaps the most promising is through deep learning.

With a sufficient amount of data from EEG signals of the subject, one can create a dataset that shows the EEG signature of the brain of the subject. This will show the behaviour of a specific brain reacting to specific stimulus, or communicating a specific thought. A deep learning neural network can use this data to learn what response is expected when a certain EEG signal is detected. The end result would be a system that would be able to understand EEG signals and produce the desired response.

II. Literature Survey

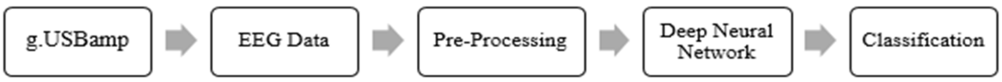
Research conducted at Stanford university to enable users to convert thoughts to text is perhaps one of the most successful implementations of a brain computer interface. This method receives thought related to handwriting, which it is able to interpret and convert into text. The user thinks of writing the letter while staring at a square within which to write it. The device reads the EEG signal and processes it, converting it into a typed letter. This method is far more accurate and efficient than the previous methods for typing without the use of hands. This process is further accelerated using autocorrect and other augmentation methods. The goal of this technology is to help disabled people communicate more effectively both to people and to a computer [9].

A team of researchers at Caltech and USC aimed to develop a brain computer interface to help quadriplegic patients to regain some of their motor functions. The experiment consisted of EEG sensors to record brain activity, a feature extractor and a decoder to interpret the signal, and some device to communicate the result to [5].

This paper outlined an effective method of implementing a brain computer interface with a less complex model. With simple feature extraction and decoding, the researchers were able to create a model that was capable of understanding the thoughts and operating devices as simple as wheelchairs as well as complex apparatus such as a robotic arm. From this paper, it is evident that one can use brain signals to achieve accurate and complex classification.

In Southeast University, Nanjing, China, researchers have developed a portable brain computer interface using convolutional neural networks. This paper integrated IoT with deep learning to develop an apparatus that was able to use a convolutional neural network to classify brain signals [10]. From this research, it is evident that deep learning can further augment the capabilities of BCI technology.

III. Proposed Methodology



Thispapersought to use cognitive data, collected using a g.USBamp, to train a deep neural network. This network was built to learn from the cognitive data to predict the wearer's thoughts, thereby translating these thoughts into machine actuation.

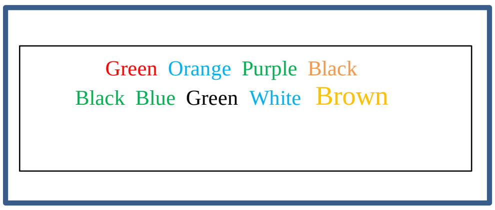


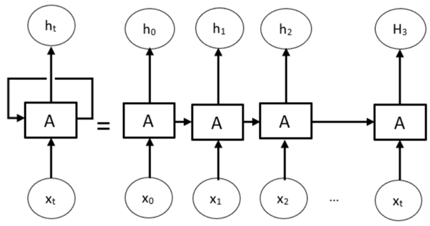
Figure 1: Subjects were asked to identify the colour of the text

Subjects were chosen to perform various cognitive challenges while wearing a G-Nautilus brain cap. These challenges ranged from basic mathematical problems to challenges involving reading coloured text that read a different colour than the one it was shaded (fig. 1). These challenges were designed to activate the brain and provide significant cognitive stimulation for the EEG sensors to pick up.

IV. TRAINING RECURSIVE NEURAL NETWORKS FOR EEG CLASSIFICATION

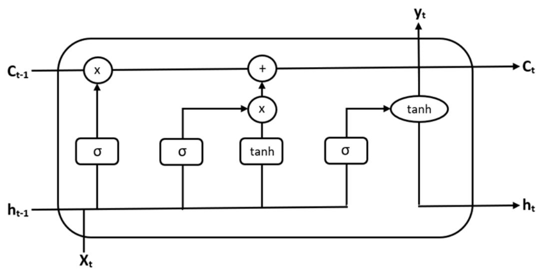
Three deep neural networks were tested to determine which performed best for the data at hand. These models were built with python using the Keras library. The models that were tested are: Simple RNN, LSTM and GRU.

Simple RNN: A recurrent neural network, or RNN, is a deep neural network that uses the previous inputs to classify the next input. This is based on the premise that the previous result may have a bearing on the next result in certain scenarios. For this reason, we must store the previous result(s) in some temporary memory to use later. When the next input is fed into the network, it uses the results of previous inputs as well as the current input to perform classification [2].



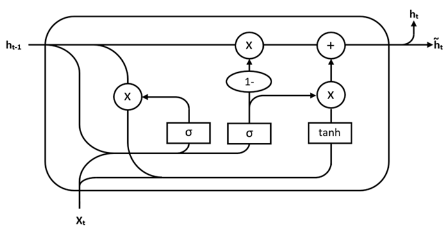
LSTM: LSTM, or long short-term memory, is a model that works in much the same way as RNN, but with one very significant improvement. RNN was subject to gradient explosion or vanishing because of multiplying the previous values repeatedly. When values were less that 1, they began to rapidly reduce to zero, and when they were greater than 1, they tended to explode to infinity when multiplied several times.

The LSTM solved this problem by using 3 gates: input gate, forget gate and candidate gate (also referred to as the gate gate). Essentially, the model uses sigmoid or tan functions of the input at every stage in order to mitigate the gradient explosion or vanishing. In doing so, this architecture is far more robust and capable of handling large volumes of data in larger neural networks. Moreover, this architecture has the ability to forget irrelevant information so that only the past values that actually affect the present data are taken into account [2].



GRU: Gated Recurrent Unit or GRU works to achieve the same goal as LSTM networks. It achieves these ends with the help of 2 gates: update and reset. This is a relatively simpler architecture than the LSTM architecture, but it has proved to be equally powerful and capable of handling complex problems.

The update gate is used to determine how much of the past information is needed to predict the future outputs. Based on this, we can get rid of any information that is no longer relevant (too old) to help in classification. This eliminates the risk of the vanishing gradient problem. The reset gate is then used to determine how much past information can be forgotten. This reduces the amount of memory necessary by getting rid of irrelevant data [3].



V. RESULTS

Below are the results for all 3 neural network models. The tables show the training accuracy, validation accuracy and test accuracy for each neural network model. Each table is dedicated to each type of neural network model, and compares the number of layers to the performance of the network. The training accuracy shows how well the model performs on the data it is trained on. This is important as it sets a baseline value for what the model knows about the data it has already learned. The validation accuracy shows us how well the model performs in each epoch, and helps select the best model. Finally, the test accuracy shows how well the model is able to generalize and classify unfamiliar data. This is the most important metric as it shows us whether or not the model is overfit for the training data. It is important to ensure that we have a high test accuracy above anything else.

TABLE I: PERFORMANCE EVALUATION OF RNN ARCHITECTURE

Number of Layers	**Training Accuracy**	**Validation Accuracy**	**Test Accuracy**
1	56.52%	58.11%	65.81%
2	76.76%	78.60%	79.22%
3	79.21%	81.49%	80.97%
4	76.52%	81.17%	81.17%

TABLE II: PERFORMANCE EVALUATION OF LSTM ARCHITECTURE

Number of Layers	**Training Accuracy**	**Validation Accuracy**	**Test Accuracy**
1	61.69%	62.16%	62.27%
2	81.90%	91.61%	87.01%
3	89.89%	92.85%	84.91%
4	88.15%	89.26%	90.97%

TABLE III: PERFORMANCE EVALUATION OF GRU ARCHITECTURE

Number of Layers	**Training Accuracy**	**Validation Accuracy**	**Test Accuracy**
1	65.46%	67.17%	63.84%
2	88.59%	90.15%	86.85%
3	89.31%	90.65%	89.32%
4	88.49%	91.63%	88.01%

VI. RESULT EVALUATION

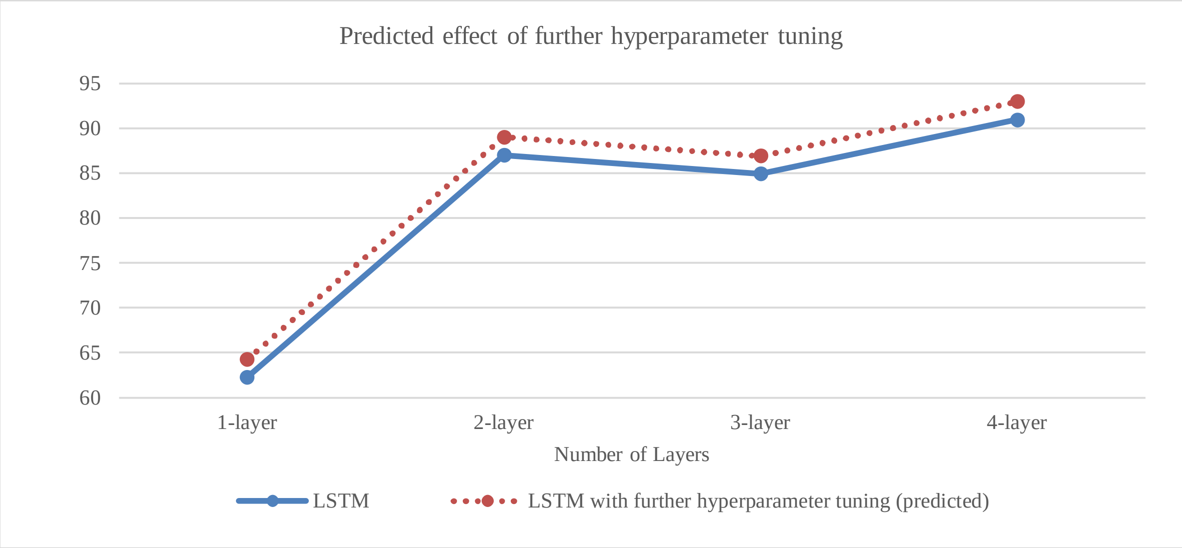
Here, we can see the close correlation between the 3 models and observe a uniform pattern of increasing accuracy with number of layers. A trendline has been drawn for the best model (LSTM), showing the potential increase in accuracy with more layers. However, this trendline is not an accurate reflection of the trend. It is more likely that the accuracy will level out at around 91-93 percent, at which point, increasing the number of layers will have no bearing on the accuracy or may even reduce the accuracy. From the results above, we can infer that there is a clear trend between the number of layers and the accuracy of the model. The greatest increase we can observe is between the 1-layer and 2-layer models, where we observe a 20% increase in accuracy among all 3 recurrent neural network models.

From the visualized data, there is a clear correlation between the number of layers and accuracy of the model. Moreover, we can see that the relationship remains uniform for all 3 models used.

Looking at the results, it is clear that the LSTM 4-layer model performed the best out of the 3. However, we cannot immediately dismiss the capabilities of the GRU architecture as it has performed almost as well as the LSTM model.

Observing the trend of the models, we can see that there is a limit to the increase in accuracy with the number of layers. Though there is a clear positive correlation, the trend appears to have an asymptote between 91 and 93 percent. At this point, increasing the number of layers will have little to no effect on the accuracy of the model.

It is possible however, to increase the accuracy by other means. By individually tuning hyper parameters such as learning rate, optimizer, etc. we can improve the accuracy of every model by some margin. While the amount of improvement one can expect is unknown, we can approximate it to be constant, and predict some amount of improvement for our model.



VII. Conclusion

This area of research is so heavily pursued because of the tremendous applications in numerous fields. This paper was carried out for the purpose of aiding differently abled people to provide simple commands to the computer. After evaluating the results of this paper, we can conclude that it has been quite successful. The models developed in this paper have proved that such neural networks are capable of being used in a brain computer interface, and can produce accurate results.

The results of this paper can be further augmented in the future through further research and application. As discussed in the results analysis, it would prove beneficial to try and optimize the hyperparameters for each model individually. This would help improve what is already the best model out of the tested models, and achieve an even more accurate classifier. Such a classifier would prove to be even more effective if deployed in a brain computer interface.

Within the scope of brain computer interfaces, the application of deep learning has hitherto been limited by a narrow view revolving around CNN architecture. However, the described methodology proves the possibility of alternative solutions with highly promising results. The exploration of recurrent neural network architectures for deployment in a brain computer interface has brought to light their potential within this field. RNN architectures, and LSTMs in particular demonstrate a high capability of classifying numeric EEG data, without the need to transform it into a 2-dimensional, image-like representation.

This paper puts forth an alternative method of EEG signal classification. For this reason alone, it has merit. The fact that the results have been positive further establishes this merit. This paper presents a new paradigm and perspective from which to view the problem of EEG signal classification, and its application within brain computer interfaces. Its success opens up a new avenue to explore and new methodologies to be implemented. Overall, this paper has been a great success and presents a wide range of possibilities in the future.

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