RECURRENT NEURAL NETWORKS ON EEG BASED CLASSIFICATION FOR BRAIN COMPUTER INTERFACE

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Abstract - Brain Computer Interface is a system that allows humans to interact with the surroundings just by brain intentions. The most successful BCI's are EEG based due to the portable non-invasive devices available. Although EEG systems have not entered the day to day life applications due the problems such as low signal to noise ratio, connectivity issues, low accuracy etc. In this paper, we introduce recurrent neural network for identifying binary class human intention on EEG time-frequency stream. The data is recorded using an Emotiv Insight 5 channel headset. A vehicular authentication system was developed using the proposed RNN classifier. In addition to this, an Android Application targeted towards disabled quadriplegic people is developed too using the proposed model.

Keywords - Brain Computer Interface, Electroencephalography, Recurrent Neural Networks, Emotiv Insight, Vehicular Authentication.

I. INTRODUCTION

Brain Computer Interfaces allows the interaction with the surrounding [7] just by an intention. Thus this technology is a boon for people with disabilities such as quadriplegic, motor disability sufferers [3, 4]. However, this technology can also be used to perform day to day activities [5, 6] such interacting with numerous devices present from a smartphone to a motor vehicle.

EEG. Electroencephalography is the method to measure brain activity for the BCI systems. The low special resolution comparing it with other techniques such as MRI, CT is not a factor affecting its popularity. This is due to the non-invasive and portable nature. When an individual thinks of an action, EEG signals on the scalp differs according to the action intended. Thus allowing the classification for a real life application.

Electrode placement on the scalp is on the basis of international system called as 10-20 system [7]. The 10 and 20 refer to percentage of the actual distances between adjacent electrodes. Using this standard allows the results to be compared and reproduce further [8].

EEG data suffers from interference due to power lines, improper connections. During data recording the movements due to muscle activity, eye blinks affect the quality of EEG signal. These are known as EEG artifacts. Techniques like Independent Component Analysis show promising results getting rid to these artifacts [10, 11]. The data goes through various pre-processing steps before the actual analysis. The preprocessing steps are discussed in the next section.

Preprocessing. Before the analysis, the raw EEG data is cleaned for the artifacts and the external noise. The preprocessing handles the power line interference, base line drift caused by movement of the electrodes on the scalp, EMG waves caused by the muscle movements and outliers if present [12].

Notch Filter. A notch filter of 50Hz is applied to eliminate the interference caused by the power lines.

High Pass Filter. There is a baseline drift in the EEG data due to movements between the scalp and the electrodes. This baseline drift is removed by using the high pass filter of cutoff frequency 0.5 Hz.

Band Pass Filter. The required EEG signals are present mainly at frequencies from 8Hz to 30Hz. The interfering EMG signals are present at higher frequencies above 60Hz. To eliminate those a passband of 2-60 Hz is used.

Six Sigma Filter. Unintended movements cause high spikes in EEG data. Such data with the outliers affect the normalization of the data. Thus samples exceeding $\pm 6\sigma(x_i)$ are set to $\pm 6\sigma(x_i)$ where σ is the standard deviation of channel i.

Frequency bands. EEG signal can be divided into several bands based on the frequency. Comparing with time domain which is a noisy signal, frequency domain signal is fairly significant. Thus the frequency band power features do the classification of mental commands efficiently [13]. The following table depicts the bands and corresponding frequency.

Frequency in Hz	EEG Bands
60-120	High Gamma
30-60	Gamma
15-30	Beta
7.5-15	Alpha
3.75-7.5	Theta
0-3.75	Delta

Table 1 Frequency Bands

II. PREVIOUS WORK

Last decade has seen an extensive research in the field of EEG decoding. Various approaches tend to show varying amount of accuracies. Most of this work revolve around the conventional machine learning approaches like Support Vector Machines (SVM), Linear Discriminant analysis (LDA).

Yong X, Menon C [1]. The presented their work classifier for same-limb movement classification based.12 healthy individuals participated for the data recording. The best results were achieved using SVM classifier. For binary classification they achieved an average accuracy of 66.9%. On introducing a third class the accuracy dropped to 60.7%.

H. Yang, S. Sakhavi, K. K. Ang and C. Guan [2]. A Filter bank common spatial pattern which generate frequency ranged EEG features. 9 individuals participated in the study which led to the classification of 4 motor imagery classes. The accuracy achieved was 67.01% (±16.20%).

Özerdem, M. S., &Polat H [14]. EEG signals recorded from 20 healthy subjects and publicly available DEAP dataset was used. Dynamic channel selection was used which lead to selection of 5 channels having the highest performances among the 32 channels with MLPNN. TO classify emotions, they used DWT feature extraction, while MLPNN and kNN have been used as classifiers.
Accuracy obtained here is 72.92%

The EEG data is time series and dynamic. Recurrent Networks have proved to be good for similar forms like natural language processing. RRNs are not extensively used for EEG classification as they are used for NLP [15].

III. LSTM

A LSTM (Long Short-term memory) is a derivation of RNN architected so as to outperform the capability of standard RNN's to process and store information. In the training phase of RNN, the back-propagated gradients can vanish due to processes using finite-precision numbers. LSTMs can fragmentally handle the 'vanishing gradient problem' by allowing gradients to flow unchanged.
LSTM has lately come up as efficient method in sequence models for processing serial data and patterns as like audio and handwriting. Alex Greaves [1], Presented that LSTM can be deployed to create complex, realistic sequences containing long range memory structure using its memory cells.
The components of a regular LSTM unit are: a cell, an input gate, an output gate and a forget gate. The values go in and out of the cell as handled by the three regulators- the gates [16, 17].

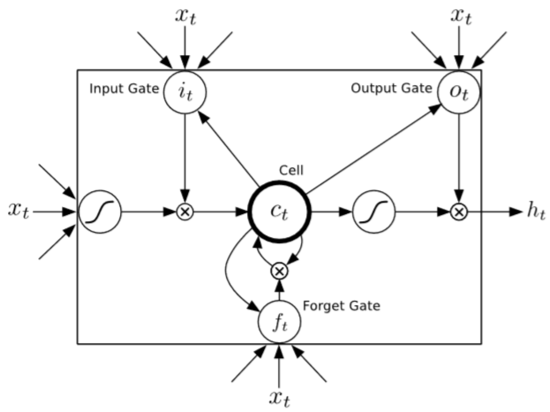

Figure 1: LSTM Cell

The compact forms LSTM equations with forget gate. In the equations below Matrices W q {\displaystyle W_{q}} Wq and U q {\displaystyle U_{q}} Uq contain, respectively, the weights of the input and recurrent connections, where the subscript *q {\displaystyle _{q}} q* can either be the input gate *i {\displaystyle i} i*, output gate *o {\displaystyle o} o*, the forget gate f {\displaystyle f} f or the memory cell c {\displaystyle c} c, depending on the activation being calculated. Thus we are using a vector notation such that, ct∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝhcontains h {\displaystyle h} h LSTM unit's cells.

ft = σg(Wfxt+ U f ht-1 + bf)
it = σg(Wi xt+ Uiht-1 + bi)
ot = σg(Wo xt+ U o ht-1 + bo)
ct = ft Ө ct-1 + it Өσc(Wcxt+ U c ht-1 + bc)
ht = otӨσh(Ct)

Where the initial values co = 0 are c 0 = 0 {\displaystyle c_{0}=0} and h0 = 0 h 0 = 0 {\displaystyle h_{0}=0} and the operator 'Ө' ∘ {\displaystyle \circ } denotes the Hadamard product (element-wise product). The subscript t t {\displaystyle t} indexes the time step.

Variables in the above expressions.
i) Input vector to the LSTM unit: xt∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝh
ii) f t ∈ R h {\displaystyle f_{t}\in \mathbb {R} ^{h}} Forget gate's activation vector: ft∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝhi t ∈ R h {\displaystyle i_{t}\in \mathbb {R} ^{h}}
iii) Input gate's activation vector: it∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝho t ∈ R h {\displaystyle o_{t}\in \mathbb {R} ^{h}}
iv) Output gate's activation vectorh t ∈ R h {\displaystyle h_{t}\in \mathbb {R} ^{h}} : ot∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝh
v) Hidden state vector also known as output vector of the LSTM unit: ht∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝh

vi) c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}}Cell state vector: ct∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝh
vii) WW ∈ R h × d {\displaystyle W\in \mathbb {R} ^{h\times d}} U ∈ R h × h {\displaystyle U\in \mathbb {R} ^{h\times h}} b ∈ R h {\displaystyle b\in \mathbb {R} ^{h}} eight matrices and bias vector parameters which need to be learned during training: W ∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝhxd ,: U ∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝhxhand : b ∈ c t ∈ R h {\displaystyle c_{t}\in \mathbb {R} ^{h}} ℝh.
Where the superscripts d {\displaystyle d} and h {\displaystyle h} refer to the number of input features and number of hidden units, respectively.

Activation functions.
i) σ g {\displaystyle \sigma _{g}} Sigmoid functionσ c {\displaystyle \sigma _{c}}:σg
ii) Hyperbolic tangent function: σc

IV. DATASET AND RECORDING

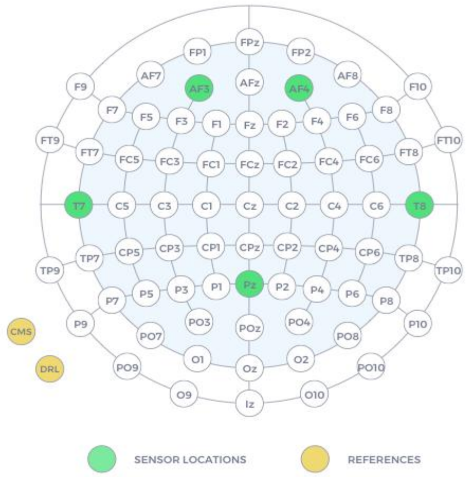

Figure 2: Electrode placements for Emotiv Insight with reference to International 10-20 System

Recording Instruments. Emotiv Insight, a 5 channel EEG headset was used for the recordings. The electrodes are placed according to 10-20 system at the locations viz. AF3, AF4, Pz, T7, T8.The reference electrode is placed behind the right ear lobe.Fig 1 shows the locations of the recording electrodes and reference electrodes.number of gate counts in group2 is determined as follows:

Recording Protocol. 15 healthy subjects from various backgrounds including engineering, music, and computer science aged from 18-22 came in for the recordings. The participants were instructed to limit external movements and imagine set of two actions at a different trial.120 trials of each participants were recorded. A fixed protocol was followed for the recordings.

A 10 second trail for each action that is for left hand movement and right hand movement was recorded. Fig 2 shows the recording protocol.

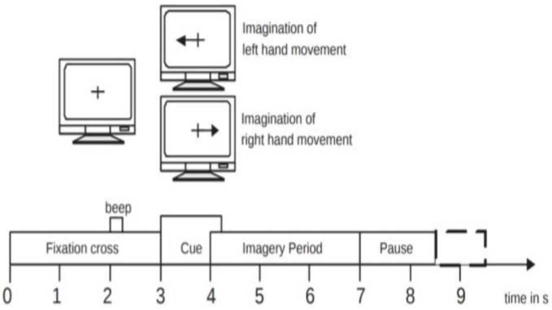

Figure 3: Recording Protocol

V. PROPOSED MODEL

Due to the drawbacks of simple RNN of the vanishing gradients, LSTM layers are used in the model. Fully connected 2 LSTM layer with a dropout layer followed by a dense layer. The dropout layer solves the problem of overfitting.
Frequency band data recorded from Emotiv Insight with the procedure mentioned above is passed as an input. The data is labelled accordingly. The frequency band data is characterized by 24 columns. The columns constitute various band power from each electrode viz. AF3, AF4, PZ, T7 and T8. The bands are theta, alpha, low beta, high beta and gamma.
The data is reshaped into (N x 1 x 24) vector where n is the number of samples and then passed to the first sequential LSTM layer. A dropout with a probability of 0.2% forms the next layer. The next layer is a LSTM with 32 neurons. The final layer is dense layer with a sigmoid activation function. Keras with tensorflow backend is used to implement the model.
The model is trained using ‘Adam’ optimizer with a binary cross entropy loss function on 500 epochs and a batch size of 20

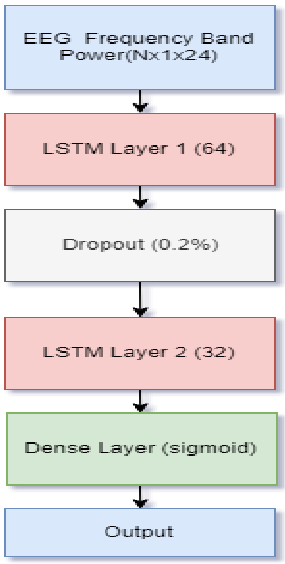

Figure 4:Proposed Model

VI. RESULTS

Comparing the conventional machine learning models (SVM, LDA) mentioned in section 1.2.The proposed model had an accuracy of 77.47%.The model performed better than the conventional models if trained on an individual data. Model performed poorly when the input feed consist of data from every individual. Thus even the model failed generalizing the data for all, it performed well on a single individual data.

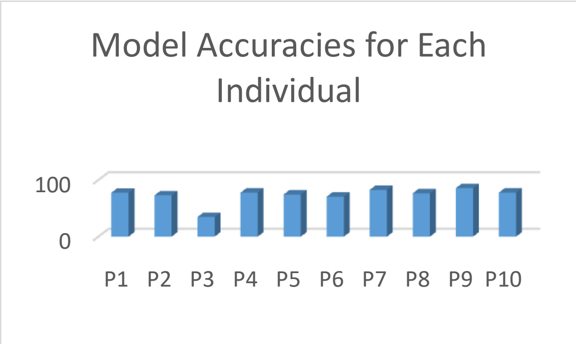

Figure 5: Model Accuracies of model trained for 10 individuals.

The model shows consistent accuracies for most of the subjects. The model tends to fail for P3, this may be the fact due the term known as BCI Illiteracy. About 20% of humans are characterized as BCI Illiterate.

VII. APPLICATIONS

1) Vehicular Authentication

The classifier was used to develop an authentication system that allows user to lock-unlock the vehicle with just an intention to do so. The user wears the EEG headset and recite the trained action, which in turns unlock-locks the vehicle.

Figure 6:Authentication Circuit installed on a Scooter

Hardware Description.
Following are the details the hardware used.

- ESPRESSIF ESP.ESP32-WROOM-32 is a powerful, generic Wi-Fi + BT + BLE MCU module that targets a wide variety of applications, ranging from low-power sensor networks to the most demanding tasks. Modules in the ESP32 WROOM Series contain the ESP32 SoC, flash memory, precision discrete components and a PCB/IPEX antenna which achieves outstanding RF performance in space-constrained applications.

- Lock Authentication Module. The module bypasses the mechanical system of vehic-ular lock by electrical system. Therefore, a key is not needed to unlock the vehicle. Mosfets IRF9530, IRF530 are used to control such a large power and to switch the vehicular lock. The battery is directly connected to this module. The circuit is power efficient uses few milliamps of current on standby.

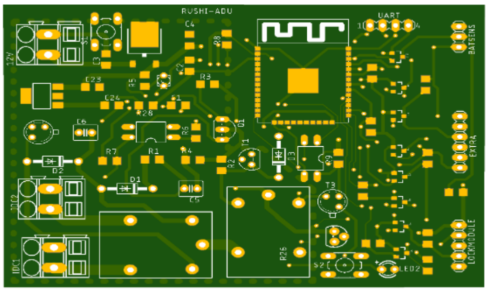

Figure 7: Lock Authentication Printed Circuit Board

- Protection Circuits. Protection circuits are very important for protection against elec-tric shock, thermal effects, overcurrent, fault currents, and overvoltage. ESP-32 con-tains a temperature sensor which is used to detect the thermal abnormalities. Opto-couplers are used between high power circuits and low power circuits. Various tech-niques are used to minimize the effect of EMI. Over voltage and current detection circuits are used. Various tests are performed on the circuits for the long term usability of modules.

2) Android Application

The proposed classifier can also be used to support an android application targeted towards people with motor disability. Any other forms of input such as touch, speech and other sensory inputs would not work in case of this application. The functioning happens only upon triggering commands using thoughts by the user wearing the device. Users can swipe the screen, call a friend, command a virtual assistant, convert commands into speech, order a taxi service, type, scroll, etc.

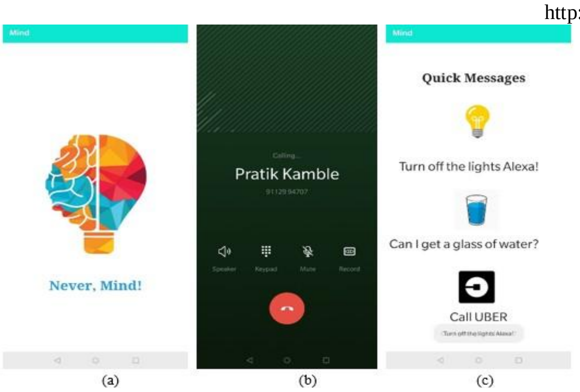

Figure 8: The three activity screens depicting different tasks available to be controlled by the brain. a) Touchless Home-screen b) Call Action c) Select Action Menu

Working: The model deployed in TensorFlow is compressed into a flat buffer with the TensorFlow Lite Converter. The compressed <.tflite> file is then loaded into a mobile or embedded device. We then quantize it by converting 32-bit floats to more efficient 8-bit integers as they are now running on low computing power devices. Fig. 8 explains the detail architecture for the deployment.

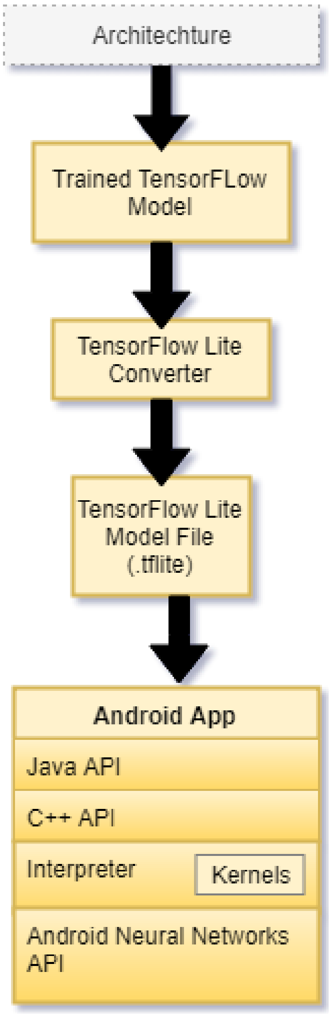

Figure 9: Architecture Diagram for deploying the trained model.

VIII. CONCLUSION

The RRN-LSTM models can be used extensively for EEG data also in addition to NLP. The proposed model was able to classify left hand movements vs right hand movements with an average accuracy of 77.47%.The model worked successfully when single individual data was fed. However it failed to generalize when then data from every individual was clubbed and given as an input. The work has a scope of improvement on further experimentation.

The proposed model was used to realize two applications. The vehicular authentication system and an Android Application. This work shows that EEG technology can be integrated with day to day life seamlessly. The future holds an important position for EEG technology.

REFERENCES

[1] Yong X, Menon C (2015) EEG Classification of Different Imaginary Movements within the Same Limb. PLOS ONE 10(4): e0121896.

[2] H. Yang, S. Sakhavi, K. K. Ang and C. Guan, "On the use of convolutional neural networks and augmented CSP features for multi-class motor imagery of EEG signals classification," *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan, 2015, pp. 2620-2623. doi: 10.1109/EMBC.2015.7318929.

[3] Jonathan R. Wolpaw, Dennis J. McFarland, Multichannel EEG-based brain-computer communication,Electroencephalography and Clinical Neurophysiology,Volume 90, Issue 6, 1994, Pages 444-449, ISSN 0013-4694, https://doi.org/10.1016/0013-4694(94)90135-X.

[4] P. J. Cilliers and A. J. W. Van Der Kouwe, "A VEP-based computer interface for C2-ouadriplegics," *Proceedings of the 15th Annual International Conference of the IEEE Engineering in Medicine and Biology Societ*, San Diego, CA, USA, 1993, pp. 1263-1263. doi: 10.1109/IEMBS.1993.979126

[5] Graimann, B., Allison, B. Z., &Pfurtscheller, G. (Eds.). (2010). *Brain-computer interfaces: Revolutionizing human-computer interaction*. Springer Science & Business Media.

[6] Allison B.Z., Neuper C. (2010) Could Anyone Use a BCI?. In: Tan D., Nijholt A. (eds) Brain-Computer Interfaces. Human-Computer Interaction Series. Springer, London

[7] ValerJurcak, Daisuke Tsuzuki, Ippeita Dan, 10/20, 10/10, and 10/5 systems revisited: Their validity as relative head-surface-based positioning systems, NeuroImage, Volume 34, Issue 4, 2007, Pages 1600-1611, ISSN 1053-8119,https://doi.org/10.1016/j.neuroimage.2006.09.024.

[8] Myslobodsky MS, Coppola R, Bar-Ziv J, Weinberger DR. Adequacy of the International 10-20 electrode system for computed neurophysiologic topography. J ClinNeurophysiol. 1990 Oct;7(4) 507-518. PMID: 2262544.

[9] Franc¸oisChollet et al. Keras. https://github.com/fchollet/keras, 2015

[10] Jung, T. P., Humphries, C., Lee, T. W., Makeig, S., McKeown, M. J., Iragui, V., &Sejnowski, T. J. (1998). Extended ICA removes artifacts from electroencephalographic recordings. In *Advances in neural information processing systems* (pp. 894-900).

[11] Delorme, A., Sejnowski, T., &Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *Neuroimage*, *34*(4), 1443-1449.

[12] Qian, X., Xu, Y. P., & Li, X. (2005). A CMOS continuous-time low-pass notch filter for EEG systems. *Analog Integrated Circuits and Signal Processing*, *44*(3), 231-238.

[13] Mehmood, R. M., & Lee, H. J. (2015). Exploration of prominent frequency wave in EEG signals from brain sensors network. *International Journal of Distributed Sensor Networks*, *11*(11), 386057.

[14] Özerdem, M. S., &Polat, H. (2017). Emotion recognition based on EEG features in movie clips with channel selection. *Brain informatics*, *4*(4), 241.

[15] Greaves, A. S. (2014). Classification of EEG with recurrent neural networks.

[16] Huang, Z., Xu, W., & Yu, K. (2015). Bidirectional LSTM-CRF models for sequence tagging. *arXiv preprint arXiv:1508.01991*.

[17] F. Karim, S. Majumdar, H. Darabi and S. Chen, "LSTM Fully Convolutional Networks for Time Series Classification," in *IEEE Access*, vol. 6, pp. 1662-1669, 2018. doi: 10.1109/ACCESS.2017.2779939.

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