**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

**JATIYA KABI KAZI NAZRUL ISLAM UNIVERSITY, TRISHAL**

**Date**: 28/02/2022

1. **Name of the student**: Mitu Akter

**Roll No**.: 10201001 **Session:**MS 2019/20

1. **Programme:** MS CGPA in B.Sc. (Engr.): 3.80

**Proposal for:** Thesis

1. **Name of the Proposed Supervisor: Dr. Md**

**Designation**: PROFESSOR

1. **Name of the Co-Supervisor (if any):Designation**:
2. **Date of First Enrolment in the Program:**
3. **Tentative Title (Block Letters):**

**Multi-Channel EEG Cleaning From Ocular Artifact in Brain Computer Interface Using Deep Neural Networks.**

1. **Background and present state of the problem:**

**Introduction:**

Brain-computer interface (BCI) is a collaboration between a brain and a device that enables signals from the brain to direct some external activity, such as control of a cursor or a prosthetic limb. The interface enables a direct communications pathway between the brain and the object to be controlled. In the case of cursor control, for example, the signal is transmitted directly from the brain to the mechanism directing the cursor, rather than taking the normal route through the body's neuromuscular system from the brain to the finger on a mouse.[1] Brain-Computer Interfaces (BCI) can improve the life quality of disabled individuals. For implementing BCI technology the most common method for capture signal from the brain is Electroencephalography or EEG. Electroencephalography is a method to record an electrogram of the electrical activity on the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain underneath. It is typically non-invasive, with the electrodes placed along the scalp. beating and movement of other muscle groups [8,18]. Although EEG is designed to record cerebral activity, it also records electrical activities arising from sites other than the brain which is known as artifact. To make a BCI System ready to be implemented outside controlled environment removal or cleaning of the EEG is necessary as it will increase the statistical properties of the signal generated from the brain, thus the accuracy of and effectively of the BCI system will increase.

**Background Study:**

A recorded EEG signal is highly contaminated with physiological artifacts from various sources, such as eye blinking/movements, heart. Among the artifacts signals, one of the most troublesome artifacts observed in the EEG signals are due to the ocular activity, whichare called ocular artifacts [19]. Occular artifacts can easily obscure the EEG signal, making its visual or automated neurophysiological monitor and data analysis difficult[20]. OAs removal is inevitable before the neurophysiological monitoring or data analysis of EEG. It’s true that the all kinds of algorithms aiming at recovering artifact-free signal have been investigated intensively. In the early years, the common method was to manually cut the entire segment of data affected by the OAs, which can lead to a relevant information loss [1,13].

Recently,the neural network has been applied in the Occular artifacts removal[8]. Jing Hu et al. combined the functional link neural network and adaptive neural fuzzy inference system (FLNN-ANFIS) to remove OAs and electromyogram (EMG) artifacts [26]. This method wisely constructed a filter by using FLNN and ANFIS to filter OAs and EMG artifacts, which is good at handing the vague data. These methods mentioned above both take advantage of the ability of neural network that can approximate smooth nonlinear functions. Moreover, the approximation ability of neural network is limited compared with the deep learning network.

Deep Learning networks are the mathematical models that are used to mimic the human brains as it is meant to solve the problems using unstructured data, these mathematical models are created in form of neural network that consists of neurons.[2].

1.brain-computer interface (BCI), https://www.google.com/amp/s/whatis.techtarget.com/definition/brain-computer-interface-BCI%3famp=1

2. Deep Learning Networks, https://www.educba.com/deep-learning-networks/

1. **Objectives with specific aims and possible outcome:**

**Objective:**

(Write the objectives as a list, e.g. (a).... (b)....)

**Outcomes:**

(List the outcomes of your works within 200-300 words)

1. **Outline of Methodology/ Experimental Design:** 
   * 1. **Outcome 1**: Provide a title of the outcome and describe the method that will be followed to implement the proposed work or a component of it.

***Experimental Setup:***Describe experimental processes that will be followed in implementing and experimenting for the proposal or a specific component of the proposal.

(Other than for B.Sc., this section can be comprised of several outcomes, e.g., Outcome 2:, Outcome 3:)

1. **References:**

Follow the defined style for the references with font size of 10

For journals/Transactions:

authors name separated by comma, "Title of the article", Name of the Journal/Transaction, volume.issue (published year): pages start to end

Example:

1. Kamal, A. H. M., and Mohammad M. Islam. "Enhancing embedding capacity and stego image quality by employing multi predictors." Journal of Information Security and Applications 32 (2017): 59-74

For conference proceeding articles:

Author's name separated by comma, "Title of the article", Proc. + name of the conference, pages, District/division, country, year

Example:

1. Kamal A H M and Islam M M, “Capacity Improvement of Reversible Data Hiding Scheme through Better Prediction and Double Cycle Embedding Process”, *Proc. IEEE Int Conference on Advance Networks and Telecommunication Systems,* pp. 1-6, Kolkata, India, 2015

Newspaper/Magazine:

Author's name separated by comma,"Title of the article", Name of the newspaper/magazine, country, papes, year

Example:

1. AAA, BBB, "Ethics in teaching", The daily star, Bangladesh, 4, 2018

Website:

Title, web address, last visited date

Example:

1. Trump condemns CIA Russia hacking report, http://www.bbc.com/news/world-us-canada-38292392, last visited: 20 January 2017
2. **Cost Estimate: (Mention every item which costs Tk. 200/- and more)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| (a) | Cost of Material (Breakup needed) | Tk. |  | |
| (b) | Field works (if applicable) | Tk. |  | |
| (c) | Conveyance/ Data Collection (With Breakup) | Tk. | |  |

**(Break-ups may be provided in separate sheet if necessary) Total:**

(Taka ---------------- thousand -------------hundred and -----------only)

1. **Justification of having Co-Supervisor:**
2. **Department's (Higher Study Committee) Or (Academic Committee Meeting) reference: (Filled up by HSC/Dept. Head)**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Meeting no.** | **Resolution No.** | **Date:** |

**. .**

**Signature of Applicant**

**\begin{listing}**

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[1] brain-computer interface (BCI), https://www.google.com/amp/s/whatis.techtarget.com/

definition/brain-computer-interface-BCI%3famp=1

[2] Deep Learning Networks, https://www.educba.com/deep-learning-networks/

[3] H.A.T. Nguyen, J. Musson, F. Li, et al., EOG artifact removal using a wavelet neural network, Neurocomputing 97 (2012) 374–389.

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[1] Andrew B. Schwartz, X. Tracy Cui, Douglas J. Weber, and Daniel W. Moran. Brain-Controlled Interfaces: Movement Restoration with Neural Prosthetics. Neuron, 52(1):205{220, October 2006.

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