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EVALUATION OF ARTIFICIAL NEURAL NETWORK FOR THE DEVELOPMENT OF

THE BRAIN COMPUTER INTERFACE

Diploma thesis

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Olen koostanud töö iseseisvalt. Kõik töö koostamisel kasutatud teiste autorite tööd, põhimõttelised seisukohad, kirjandusallikatest ja mujalt pärinevad andmed on viidatud.

.... Töö autori allkiri ja kuupäev

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ENGLISH ABSTRACT

The purpose of this research study was to explore the possibility of developing a Brain-Computer Interface (BCI). The main objective was that the BCI should be able to learn and classify human brain state activities by using Artificial Neural Network (ANN), with applications towards using brain activity to control devices such as computers, robots and machines. To acquire the datasets, two series of experiments were conducted with ten and six human subjects respectively. The first experiment predefined tasks assigned to each subject in order to stimulate the state of the brain by solving some logical and mathematical problems. The second experiment was created to collect Motor-Imagery (MI) datasets. The purpose of these experiments was to acquire the datasets and use them to evaluate the suitable ANN. The developed ANN4BCI software classifies state of brain activities such as thinking/resting or motor imagery/action observation. A number of open source tools with ANN support were used because they were more suitable for the specific needs and environment. As a result, this study showed that Accord.NET is the best among other open source tools which support ANN when compared to Simbrain, Scikit Learn, Weka and Shogun. The Accord.NET accuracy of calculation is 59.7% with the first series of dataset and 64% with the second series of dataset. The speed of calculation of Accord.NET is medium. The developed software, ANN4BCI, is an effective tool for research in the field of BCI.

ESTONIAN ABSTRACT

Uuringu eesmärgiks oli uurida võimalust arendada Brain-Computer Interface (BCI). Peamine eesmärk oli, et BCI oleks võimeline õppima ja klassifitseerima inimese ajutegevusi kasutades kunstlikku närvivõrgustikku (ANN), rakendusvaldkonnaks on ajuaktiivsuse kasutamine kontrollseadmetes, nagu arvutid, robotid ja masinad. Andmekogumite omandamiseks viidi läbi kaks katsete seeriat kümne ja kuue inimestega vastavalt. Esimeses katses määrati igale objektile ajuseisundi stimuleerimiseks mõned loogilised ja matemaatilised probleemid. Teine katse viidi läbi Motor-Imagery (MI) andmekogumite saamiseks. Nende katsete eesmärk oli koguda andmekogumid ja kasutada neid sobiva ANN hindamiseks. Arendatud ANN4BCI tarkvara klassifitseerib ajutegevust, näiteks mõtlemist / puhkust või motoorset kujutlemist / tegevuse vaatlust. Kasutati ANN-toega avatud lähtekoodiga tööriistu, sest need sobisid paremini konkreetsetele vajadustele ja keskkonnale. Uuringutulemused näitasid, et Accord.NET on parim avatud lähtekoodiga tööriist, mis toetab ANN, võrreldes Simbrain, Scikit Learn, Weka ja Shoguniga. Accord.NETi arvutamise täpsus on 59,7% esimese andmekogumi seeria ja 64% teise andmekogumi seeria puhul. Accord.NETi arvutamise kiirus on keskmine. Arendatud tarkvara ANN4BCI on tõhus vahend BCI valdkonna uurimiseks.

1. INTRODUCTION

This research study examined EEG sensor abilities to use as a new interface to receive information as well as to control any device. The topic was chosen in order to investigate the use of brain activity to control devices such as computers, robots, and machines. It is a relevant topic nowadays because Artificial Intelligence (AI)/machine learning (ML) has received great attention for the development of Brain Computer Interface (BCI) applications to solve difficult problems in several fields such as medical science and robotics. A lot of work has been done in the last 20 years in the research field of BCI. Nevertheless, the bioengineering branch is relatively young so there is not much research done in this field yet. This research study focused on available artificial neural network (ANN) open source algorithms in order to analyse and choose the best ANN open source algorithm for EEG signals to classify brain activities such as thinking/resting or motor imagery/action observation.

Our research group already developed a fully working application for obtaining the EEG signals through Bitronics. Bitronics is a device used to conduct the experiments and acquire the needed datasets. (Yar M., Daniil V. 2019) The Bitronics EEG is a single-channel EEG compatible Arduino module. Its big advantage is that it is possible to make use of dry electrodes and it can use two electrodes simultaneously as a differential input, which effectively eliminates interference[1] The software can obtain human brain activities' amplitudes, but the aim of this research was to enhance the functionalities and accuracy of the results of existing software BCIANNET version 2.0.0.1 such as classification accuracy, learning speed, saving the acquired datasets and a controller which shows the state of subject.

A protocol was created to conduct the experiments to make the exact division of the state of brain activity. Later the acquired datasets were used to analyse and classify the best ANN among all available open source ANN.

The following parameters of the ANN were considered and rated. The generated results were analysed for classification:

1   Speed of calculations - because the aim is to connect Bitronics to human head and acquire the brain activities in real-time for the BCI software.

2   Accuracy of calculations.

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[1] Bitronics http://www.bitronicslab.com/store/ (28.02.2019)

3   System requirements – use the minimum system requirements to avoid high resources for calculation.

As a result, acquired EEG datasets analysed and compared with five available ANN i.e. Simbrain[2], Scikit Learn[3], Accord.Net[4], Shogun[5] and Weka[6] and found that Accord.NET is the most suitable ANN for the above-mentioned problem.

The rest of this paper is structured as follows. Section 2 presents the literature overview. Section 3 presents the procedure how to acquire the datasets, acquisition of datasets, analysis and comparison of software. Section 4 demonstrates the results which are achieved through the classification of the ANN for the development of ANN4BCI software. Section 5 presents the discussion and short overview of the results. Section 6 presents plans for future work.

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[2] Simbrain https://www.simbrain.net/ (25.02.2019)
[3] Scikit Learn https://scikit-learn.org/stable/tutorial/basic/tutorial.html (25.02.2019)
[4] Accordю.NET http://accord-framework.net/intro.html (25.02.2019)
[5] Shogun http://www.shogun-toolbox.org/mission (25.02.2019)
[6] WEKA https://www.cs.waikato.ac.nz/ml/weka/Witten_et_al_2016_appendix.pdf (25.02.2019)

2. LITERATURE OVERVIEW

A research article has been published about the comparison of all BCI spellers since 2010. (Aya R. et al2018) The paper consolidated the best BCI speller and discussed some other older systems which are built explicitly for spelling purposes. The meaning of this research is to illustrate and highlight different spellers and present them in one review. The presented speller systems are categorized according to major BCI paradigms: P300, steady-state visual evoked potential (SSVEP), and motor imagery (MI). There is no objective comparison between different spellers, as each has its variables, parameters, and conditions. However, the gathered information and the provided taxonomy about different BCI-spellers can be helpful, as it could identify suitable systems for first-hand users, as well as opportunities for development and learning from previous studies for BCI researchers.

Many researchers explore how to develop BCI and classify the brain activity. (Pavlovski V., Soldatenkova E 2017) A research study from the Moscow Institute of Physics and Technology described a BCI which can control the exoskeleton. The structure of their study is as follows:

1. Get the brain map of the patient

2. Build the bioelectrical model of activity

3. Create software for controlling data flow and analysing procedures

As a result, they have achieved a workable BCI by scanning the brain map with EMOTIV Epoc. This research does not describe any processes on how to achieve the same result in a different environment. The useful information about the data structure model was taken to show how to organize a database, and what to pay attention to in order to identify moving commands from the brain. They created a bioelectrical model and discussed how the brain is connected to parts of the human body and how the body parts are controlled by neurons. In this research study, the Scikit Learn ANN is used, which also inspired its use in this study as an open source ANN to classify brain activity.

As a result of the estimation of human emotions' role in the development of modern brain-computer interface, devices like the Emotiv EPOC+ headset are presented (Roberto S. et al 2018). The paper presented an experiment to assess the classification accuracy of the emotional states provided by the headset's application programming interface (API). In this research experiment, several sets of images selected from the International Affective Picture System

(IAPS) dataset were shown to sixteen participants wearing the headset. Firstly, the participants responded in the form of a self-assessment manikin questionnaire and the emotions elicited are compared to the validated IAPS predefined valence, arousal and dominance values. After statistically demonstrating that the responses were highly correlated with the IAPS values, several artificial neural networks based on the multilayer perceptron architecture were tested to calculate the classification accuracy of the Emotiv EPOC+ API emotional outcomes. The best result was obtained for an ANN configuration with three hidden layers and 30, 8 and 3 neurons for layers 1, 2 and 3 respectively. This configuration offers 85% classification accuracy, which means that the emotional estimation provided by the headset can be used with high confidence in real-time applications that are based on users' emotional states. Thus, the emotional states given by the headset's API may be used with no further processing of the electroencephalogram signals acquired from the scalp, which would add to the level of difficulty. This research relates to the present research because it describes some parts and parameters of ANN which will be used next.

In the work on classifying EEG, signals with ANN were investigated to classify the normal and epileptic state of the brain. (Ling G. et al 2009) Several datasets were used in this study. ANN showed an accuracy of more than 92%. The result of this research means two things:

1. ANN can efficiently classify and recognize states of brain by EEG datasets. This means that using ANN to classify EEG signals is a suitable approach.

2. Two different states of the human brain are possible to classify easily. This means that focus in datasets gathering in the present study should be targeted to collecting two opposite states of brain. Because epileptic signals are not in the scope of this research, the next experiments were targeted to collect the thinking and the resting state.

Another study had a focus to classify raw EEG amplitude without separating it into different wave forms such as Alpha, Beta and Delta etc. (Yoshioka M. et al 2014) In the current study, datasets were collected with BCIANNET version 2.0.0.1 which can divide the raw amplitude into Alpha, Beta 0, Beta 1, Beta 2 and Delta waves, so ANN classifying is optimized.

In another study, the focus was given to the classification of β (Beta) and μ (Mu) waves to control a robotic arm. (Oganesyan V et al 2017) The short-time fast Fourier transform (STFFT) was used to develop a BCI to control the robotic arm. This study concluded that the specific features of the human brain cannot concentrate for a long time, which means that future BCI needs to handle this problem and learn to predict all of the subject's brain activity. This research

was very useful because it showed the fact that if a subject only imagines some activity but does not do the real activity, the EEG signals amplitude is as not high when the subject actually does the real activity. These findings are used in research so that real logical and mathematical tasks were given to the subjects to stimulate the brain state to change the state from resting to thinking and vice versa.

In another study controlling the computers with brain's Rhythms/Electrical activity using ANN was investigated. (Yar M., Daniil V. 2019) The aim of the research study was to classify EEG waves from measured datasets. Different algorithms were used to identify which one is more suitable for classification of brain activity. The findings of the research study showed that the Levenberg Marquardt algorithm is better. Based on Levenberg Marquardt, BCIANNET 2.0.0.1 software was developed for BCI. This research group is continuing work to develop an advance version of the BCIANNET 2.0.0.1 to control devices such as computers, robots, machines. During the research twelve subjects were measured to collect the appropriate datasets in order to analyse and identify the best appropriate algorithms for the classification of brain activity.

As a result, the BCIANNET 2.0.0.1 software was developed and it collects EEG data in real time, divides it into α, β and δ (Delta) waves by frequency, and measures the waves' amplitudes. It classifies the brain waves. This data was used to teach ANN which should predict brain states (0 or 1). The main topic of this research was that they were focused on any kind of algorithm for the classification of the EEG signals. This study enhanced the BCIANNET version 2.0.0.1 by using different appropriate ANN based on parameters to improve the accuracy, speed and minimum usage of resources.

Other researchers discuss the classifying optimization in general (Farzan M. et al 2017), optimization with cardio sensors (Agapov S. et al 2017), compare the different methods of classification (Agapov S. et al 2017) (Ruanet V. et al 2007), nonlinear analysis approach for investigating EEG signals. (Yoshioka M. et al 2014) Simbrain, Weka and Shogun were used in the test because they fit our parameters and are open source and we used them for the classification of given datasets. Based on the literature overview and its application, it was decided to use the following open source tools which support the ANN to analyse and identify the performance based on given parameters to classify the brain activity:

1. Simbrain - application for machine learning with neural network support

2. Scikit Learn - machine learning library with neural network support for Python

3. Accord.NET - machine learning library with neural network support for C#

4. Shogun - machine learning library with neural network support for multiple coding languages

5. Weka - application for machine learning with neural network support

3. MATERIALS AND METHODS

3.1 Procedure to acquire the datasets

This section describes the procedure for the acquisition of the datasets. A predefined procedure is used, and each subject is instructed before conducting the experiments. The first series of experiments were conducted with ten and second series of experiments were conducted with six subjects. The ages of the subjects varied from 11 to 43 years. The following steps were taken in the process of acquiring of the EEG datasets:

1. Experimental procedures were explained to and signatures were taken from the subjects. The required information was collected from each subject such as age, gender, health status, job, contact info.

2. Subjects were seated in a chair with the Bitronics helmet on their heads.

3. The author explained the predefined criteria such as that the subject should not move, laugh, talk, scratch, has to be in the same position until the experiment is finished and must focus on the tasks.

4. Configure all necessary devices and equipment and finally quick test the environment before starting with real acquisition of EEG signals. The setup is depicted in Figure 3.

5. Start the acquisition of datasets, the starting time is noted. The tasks were given to the subject. The given tasks are attached in Appendix A and B. The datasets were stored in CSV format in a computer.

6. The CSV (comma-separated values) file is checked to confirm that the dataset was properly stored.

The objective of the experiment was to collect the EEG signals where brain activity is seen. It was very important to analyse and classify the performance of ANN based on given

tasks. In other words, the aim of the experiment was to see the different activities and states of the brain.

3.2 First series of experiments

A Power Point presentation was created with six different tasks. The tasks were easier and more difficult to stimulate the brain activity (resting/thinking). The first task was easier to start from resting because the subject first needed time to adjust and adapt to the environment. The second task was a bit more difficult to stimulate the brain activity. Resting tasks had some beautiful and static pictures to avoid eye movement because any movement introduces noise to the datasets. To stimulate the brain activity and make the subject think, logical and mathematical tasks were given. All problems were quite easy because the aim was for the subject to be able to solve the problem and to change the state of the brain. The list of tasks is provided in Appendix A. The reason for creating an experiment like this is because it is a good methodology which was learnt from previously done research work. There were 6 tasks in total, ~ 100 seconds were given to each task and altogether ~ 600 seconds elapsed. As a result, ~6,000 rows of data were collected for each dataset. In total the experiment took ±10 minutes, because of the following reasons:

1. The first reason was that tasks were controlled manually by the experimenter.

2. The second reason was to save 10 rows of data in second dataset.

3. The third reason was that Bitronics was not very comfortable for the subjects.

3.3 Second series of experiments

The second experiment was targeted to collect data about Motor-Imagery (MI). The rules and conditions were the same as listed in the procedures to acquire the datasets, but the tasks and the experiment time were changed. The tasks of this series are listed in Appendix B. In the screenshot pictures from a video, the subjects were asked to imagine this activity in their own mind and the results are shown. After that, First Person View (FPV) videos were shown. In this part, each subject was asked to be an action observer and try to replicate the activity in the video. The reason was to differentiate the brain activities and status. The standard idea in BCI is the translation of user's intention via mental imagination of motor movement, which serves as an interface through which to communicate the user's intention without limb movement. The literature survey (13) showed that the human brain cannot concentrate on one thing for a long time, so the time for each task was shortened to 60 seconds.

3.4 Preparation of the setup for experiment

The required environment was set up for each subject. They had a comfortable chair, proper light, and the tasks were displayed in front of the subject on a laptop screen at a comfortable distance. Figure 1. shows the experimental environment and Figure 2. shows the recording of the subject. Before recording, each subject had some time to get used to Bitronics and all the information and requirements were clearly explained to each subject.

Figure 1. The experimental environment.

Figure 1. shows that the subject is ready to start the experiment. The grey wire from the Arduino transfers all data to the computer, the Arduino is connected to the EEG module, and EEG module is connected to the Bitronics helmet on the subject.
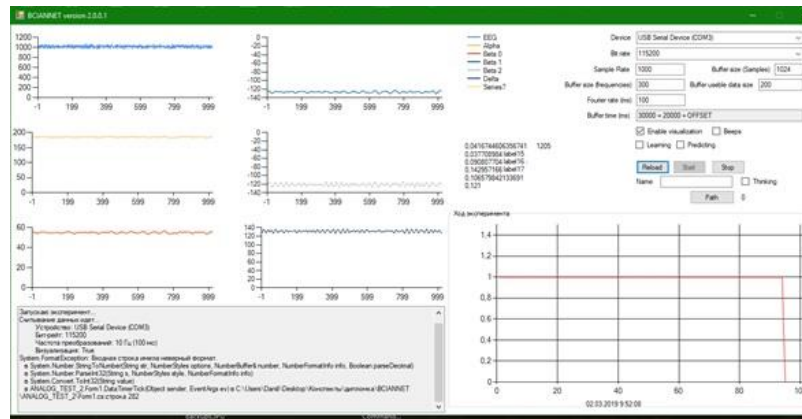

Figure 2. The unconfigured state of software to obtaining signals.

To configure the device to get the best EEG signals before starting each experiment, the board of Bitronics was configured manually by potentiometers and the electrodes position configuring is to get amplitudes. This is depicted in Figures 3 and 4. The potentiometers have different configurations. GaiN filter is a low-pass filter. Noise filter is a filter which allows

controlling the amplitude of signal, such as increasing or decreasing the amplitude. The configuration of the experiments is depicted in Figure 5.
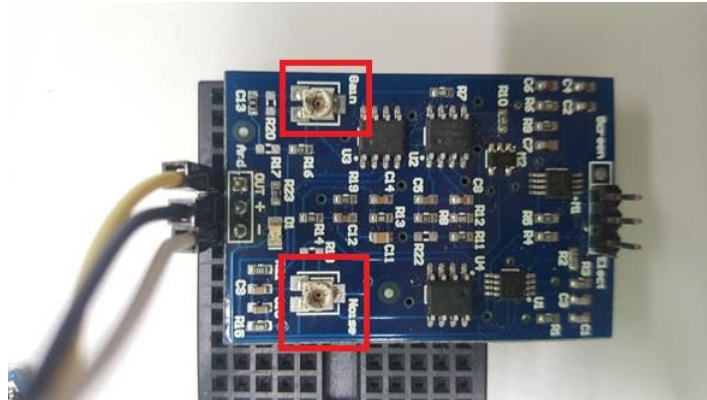
Figure 3. EEG module pins configuration. Red rectangles are potentiometers, they allow regulating noise level and signal adjustment.
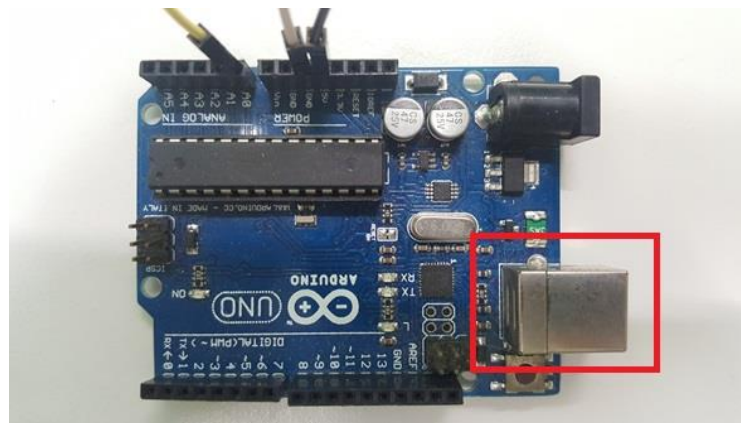
Figure 4. An Arduino pins configuration. Red rectangle-USB port which transfer the data to computer. This plate reads signals from EEG module and transfers through USB port to computer.

Before recording a new dataset, the experimenter tested all the programs and settings to avoid any of problems which may occur during the experiment. The first experiment showed that the plugged-in power cable to notebook made noises, so the cable needed to be unplugged every time.

3.5 Experiment Subjects

Before each experiment, each subject was informed about the nature of the experiments and how the data will be used in future, all subjects agreed and signed the agreement for this experiment. Ten human subjects took part in first series of experiments. The mean value of age was calculated from ten subjects. The mean value of age is 23, minimum age was 11 years and maximum age was 43 years. Most of the subjects were students and their health status was good. 5 female and 5 male subjects were involved in the experiment. Individual subjects' descriptions are shown in Table 1.

Table 1. shows the statistics of ten subjects in the experiment.

Subject #	Gender	Age	Health status	Job
Subject 1	Female	22	Good	Student
Subject 2	Male	20	Good	Student
Subject 3	Male	16	Good	Student
Subject 4	Female	19	Good	Student
Subject 5	Female	20	Good	Worker
Subject 6	Female	11	Good	Student
Subject 7	Male	21	Good	Student
Subject 8	Male	18	Good	Student
Subject 9	Female	42	Good	Teacher
Subject 10	Male	43	Good	Manager

Summary	
Total # of Subjects:	10
Mean Value of Age:	23 years
Minimum Age:	11 years
Maximum Age:	43 years
Female:	5
Male:	5

Six human subjects took part in the second series of experiments. The mean value of age was calculated from six subjects. The mean value of age was 20.8, minimum age was 18 years and maximum age was 23 years. Most of the subjects were students and health status was good. 3 female and 3 male subjects were involved in the experiment. Individual subjects' descriptions are shown in Table 2.

Table 2. shows the statistics of subjects in the second experiment.

Subject #	Gender	Age	Health status	Job
Subject 1	Female	21	Good	Worker
Subject 2	Male	21	Tooth pain	Student
Subject 3	Male	20	Good	Student
Subject 4	Male	22	Good	Student
Subject 5	Female	18	Good	Worker
Subject 6	Female	23	Good	Student
Summary				
Total # of Subjects:	6			
Mean Value of Age:	20.8 years			
Minimum Age:	18 years			
Maximum Age:	23 years			
Female:	3			
Male:	3			

3.6 Methodology

The following steps were taken in order to analyse and identify the performance of ANN based on above-mentioned parameters which are discussed in the chapter Introduction:

1. Quickly checked and initially tested the BCIANNET version 2.0.0.1 software to make sure that everything is configured and set up for acquisition of EEG signals.
2. Started with real experiments to collect datasets of brain activity.
3. Manually analysed the collected EEG datasets.
4. Collected datasets were used as input to ANN: Scikit Learn, Shogun, Weka, Accord.NET and Simbrain.
5. Identified and compared the performance of ANN based on predefined parameters which are listed in the chapter Introduction.
6. The performance of ANN is analysed. ANN performance is shown in Tables 3 and 4.
7. Finally, based on the performance, the ANN is chosen to develop the software.

3.6.1 BCIANNET updated with some needed features

On this step, the experimenter started to work with existing BCIANNET software. BCIANNET software was only able to obtain brain signals because BCIANNET software does not have a controller (I/O) to identify brain activity states. The BCIANNET software does not have the possibility to save the datasets with an appropriate name and in the appropriate location.

As the first step, a feature to save files with an appropriate name and to the appropriate location was added in order to use the obtained datasets later. The second step was adding the controller which helps during the acquisition of datasets to identify the state of brain (thinking/resting, motor imagery/action observation) which is depicted in Figure 5. The proposed solution is very simple and is enough to cover the needs in this study. The controller itself is only a check box, it was checked (1)/unchecked (0) by the experimenter during the experiment based on nature of the task. In the case of the first series of experiments, if a task is difficult, the checkbox will be checked (1), if easier then checkbox will be unchecked (0). In the acquired datasets, additional information 1 (one) was added to the file, which means that now subjects are performing a thinking task. If the controller was unchecked in the software, the added value is 0 (zero), which means that now the subject is resting. In the case of the second series of experiments, if the task is to observe the action, the checkbox will be checked (1), if task is motor imagery then checkbox will be unchecked (0). In the acquired datasets, additional information 1 (one) was added to the files, which means that now the subjects are trying to observe an action. If the controller was unchecked in software, the added value is 0(zero), which means that now the subject is imagining how does the activity.

According to the experiment plans, it was necessary to show all tasks to the subject on separate screens and on another computer a software was running to check and uncheck the controller based on given tasks to the subject.
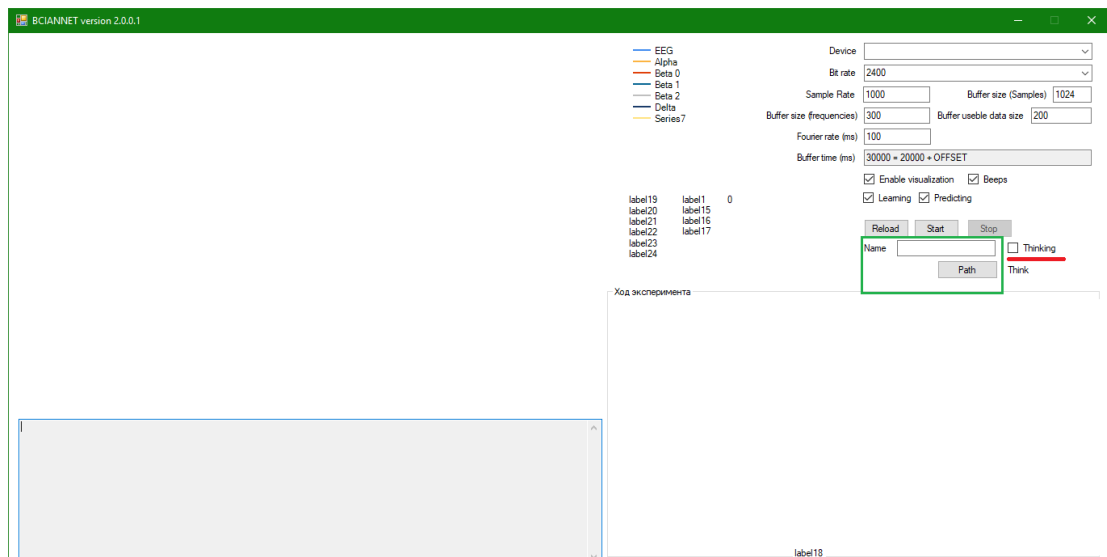
Figure 5. Updated version of BCIANNET 2.0.0.1. Green- saving functionality, Red-controller checkbox and under the red line- the state of brain activity.

3.6.2 Open source software comparison

The following ANN open sources were considered during this research study. These ANN were implemented, tested, analysed and compared based on specific parameters which are listed in the chapter Introduction. The aim was to classify suitable ANN for the development of BCI. The ANN listed and discussed in Literature Overview are:

- Scikit Learn
- Simbrain
- Shogun
- Accord.NET
- Weka

ANN was installed and some tasks were quickly tested to understand how to use ANN and identify the suitability of ANN. As a result, software is developed based on suitable ANN in order to classify the brain activity. Console environment is used for the implementation of ANN to analyse the performance of ANN in order to avoid graphical user interface (GUI) to minimize the usage of resource. The following three steps were performed with each ANN:

1. Quick teaching – ANN learned based on only one brain data dataset. The purpose of this step was to quickly check the hidden problems with the dataset because different networks read the dataset differently. The most common problem was the separator such

as coma/dot [,/.] in numbers. Quick teaching step showed how fast ANN can learn and perform.

2. Complete teaching – ANN learned based on all datasets. The purpose of this step was to identify the performance of ANN with all acquired datasets from all subjects. Execution time was noted which is listed in Table 1 such as slow or fast.

3. Prediction of ANN - on this step after teaching to each ANN. All the datasets were given without any information about the state of brain. ANN was put to test to calculate the probability of each row in a given dataset to predict the state of brain. From this step accuracy of calculations was collected which is shown in the Table 2 (Accuracy of calculation (medium of all datasets)).

4. RESULTS

4.1 Results of experiments

In total 22 of experiments were conducted with 10 subjects in the first series of experiments. The number of datasets is bigger than the number of subjects because some subjects participated only once, some of them two or three times. Ultimately, 17 datasets were used. At the end of the second series of experiments, there were in total 6 datasets from 6 subjects. Some experiments failed because of reasons such as technical problems, subjects broke the predefined rules etc. These datasets would be useful for future need, e.g. to use them for future development of BCI or any other needs. The acquired datasets are good because they have different amplitudes. The amplitudes correspond to given tasks to the subjects. Such variation makes learning much more efficient. One of the EEG datasets is demonstrated in Figure 6. which is a graphical representation of the entire dataset (~10 min) from the first series of experiments and the second series of experiments are illustrated in Figure 7.
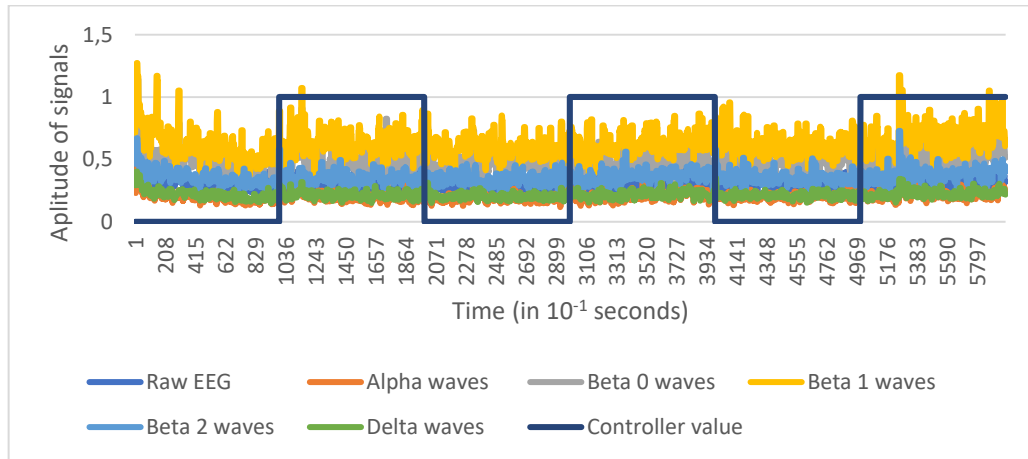
Figure 6. Graphical representation of EEG raw dataset with control value from the first series of experiments.

Figure 6. vertical axis represents the amplitude of the signals. Dark blue (analogue-like) line shows I/O from the controller. Where the line is at level 0, it means that the subject is resting, and the controller is unchecked. Dark blue line being at level 1 means that the subject tries to solve some mathematical or logical tasks, so it means that the subject is thinking. In Figure 6. horizontal axis time is 10^{-1} seconds.
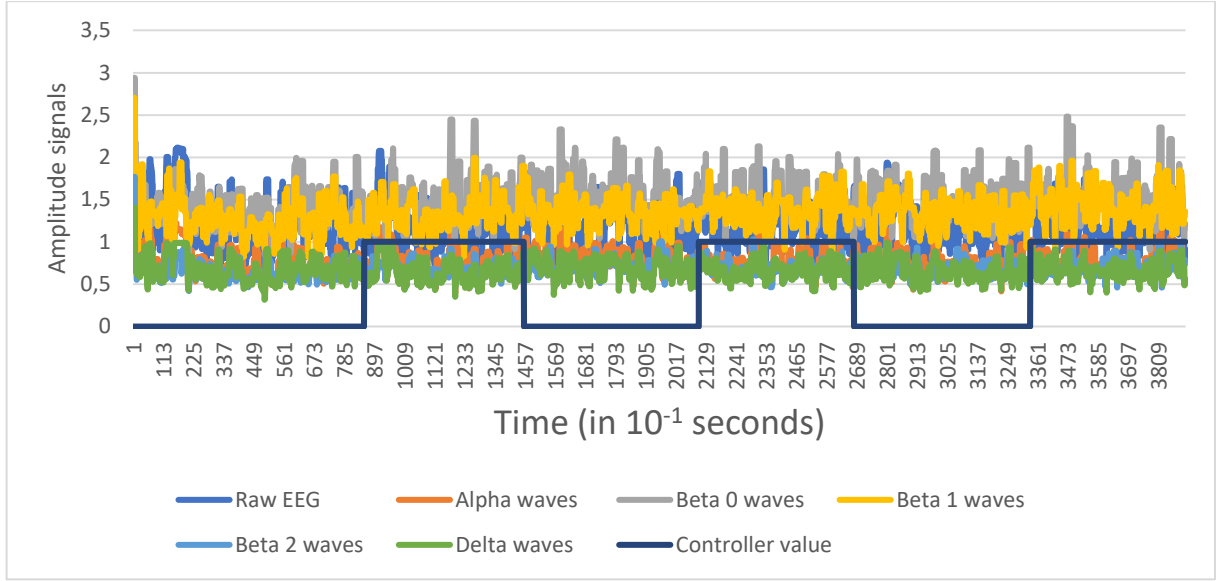
Figure 7. Graphical representation of EEG datasets with control value from the second series of experiments.

Figure 7. vertical axis represents the amplitude of the signals. Dark blue (analogue-like) line shows I/O from the controller. Where the line is at level 0, it means that the subject imagines the activity and the controller is unchecked, and the dark blue line at level 1 means that the subject is watching an FPV video, so it means that subject is in action observation. In Figure 7. horizontal axis time is 10^{-1} seconds.

Figure 8. shows which data was used in ANN tests. Black line is experiment total time. Orange lines show each task's place on the timeline, numbers show start and end times of each task.
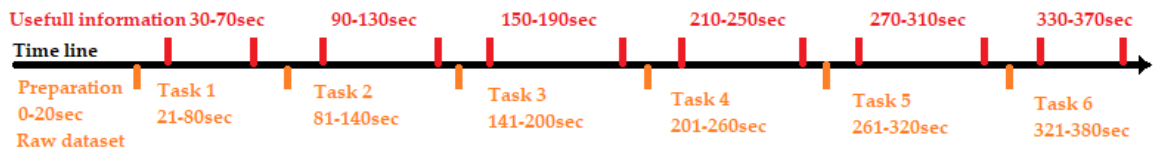
Figure 8. Taken data from second series of experiments

Red lines show which data was taken to final dataset, numbers show which period was taken to final dataset. The reason of cutting data is because each subject knew when the task ended, so the subject may start to think about other things than the task. Also, when each task starts the subject needs switch on new a target after the previous step. Preparation part was deleted totally from final dataset because this part is not a task and it was necessary for us to adjust to the subject in the environment and configure and test EEG module.

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4.2 Classification of ANN

Five ANN listed in Table 3. are tested, analysed, compared based on the defined parameters which are listed in the chapter Introduction. The acquired 17 datasets were used with each ANN and the performance is noted and listed in Table 3. Three steps were used which are mentioned in 3.4.2 (1. Quick teaching, 2. Complete teaching and 3. Prediction of ANN) to analyse the performance of each ANN. As a result, the best suitable ANN was C# library "Accord.NET" which fits the final goal of developing a BCI software.

Table 3 In this table statistics about each successfully tested ANN are shown

ANN	Speed of calculation (very slow - slow - medium - fast - very fast)	Accuracy of calculation (median of all datasets)
Accord.NET	Medium	59.7 %
Scikit-Learn	Very Fast	55.4 %
Shogun	Fast	51 %
Simbrain	Very Slow	49.95 %
Weka	Slow	57 %

The table shows that Simbrain and Weka ANN are not suitable to develop BCI because they have their own GUI and the implementation is very difficult. The accuracy of the Simbrain is 49.95% and Weka 57%. Nevertheless, Simbrain is very slow which is not suitable for real-time environment. The Scikit-Learn and Shogun are quite good because both are fast and the accuracy of Scikit-Learn is 55.4% and Shogun is 51 %, but the problem is the comparability with existing BCIANNET 2.0.0.1 because the existing version is developed in .NET platform with C# programming language. The Scikit-Learn and Shogun are developed in Python. The Accord.NET ANN is medium, and accuracy is 59.7 % which is better than all other tested ANN. The Accord.NET is developed in .NET platform with C# programming language. It is much easier to use the same platform for the development of BCI in .NET platform with C# programming language and to use the available library.

Table 4 In this table statistics about each successfully tested ANN are shown

ANN	Accuracy of calculation (median of all datasets)	Speed of calculation (very slow - slow -— medium - fast - very fast)
Accord.NET	64 %	Medium
Scikit-Learn	55.4 %	Fast
Shogun	51.16 %	Very Fast
Simbrain	51.7 %	Very Slow
Weka	58.2 %	Slow

Table 4. shows the results after the second series of experiments. The main difference between the first and the second series of experiments are a) the number of subjects and b) the size of the acquired datasets.

Total amount of learnt and predicted data in the second series is much less than in the first series of experiments, because in the second series of experiments, the preparation (0-20 seconds) is deleted which was the useless information. It is shown in results that the accuracy of calculation is a little bit improved.

4.3 Development of the ANN4BCI

After the classification of ANN, the performance of Accord.NET ANN is more suitable for the development of "ANN4BCI". The ANN4BCI is developed based on Accord.NET. This study shows that Accord.NET is a more efficient tool to learn and predict brain activity such as thinking and resting as provided by different datasets. Created ANN has 6 layers, 6 neurons on input layer and 1 neuron on output layer. The ANN has 4 hidden layers. The ANN uses bipolar sigmoid function to calculate values. The developed ANN4BCI could be used as a tool for the research field of bioelectricity. The ANN4BCI has the capability to simply load the acquired datasets and finally save the predicted result. It is the most important to use the predicted result to extend the functionality which improves the classification of BCIANNET 2.0.0.1 in real-time environment. The ANN4BCI software is easy to configure in order to set up and optimize in future, based on possible needs. It has separated the functionalities for learning and predicting.

The ANN4BCI is depicted in Figure 8. The GUI is comfortable and allows to easily control all the functionalities and processes.

24
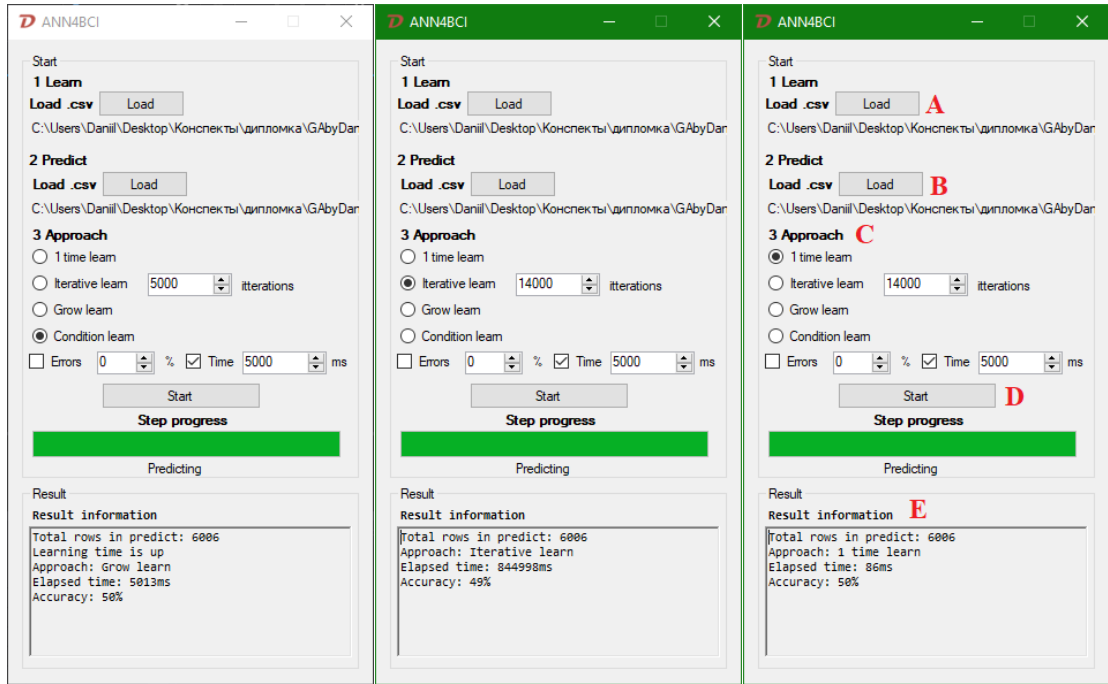
Figure 9. GUI of ANN4BCI in predicting phase. A is load dataset for Learn, B is load dataset for prediction, C chooses the approach of learning, D starts the ANN4BCI software and E is the finally generated result by ANN4BCI software.
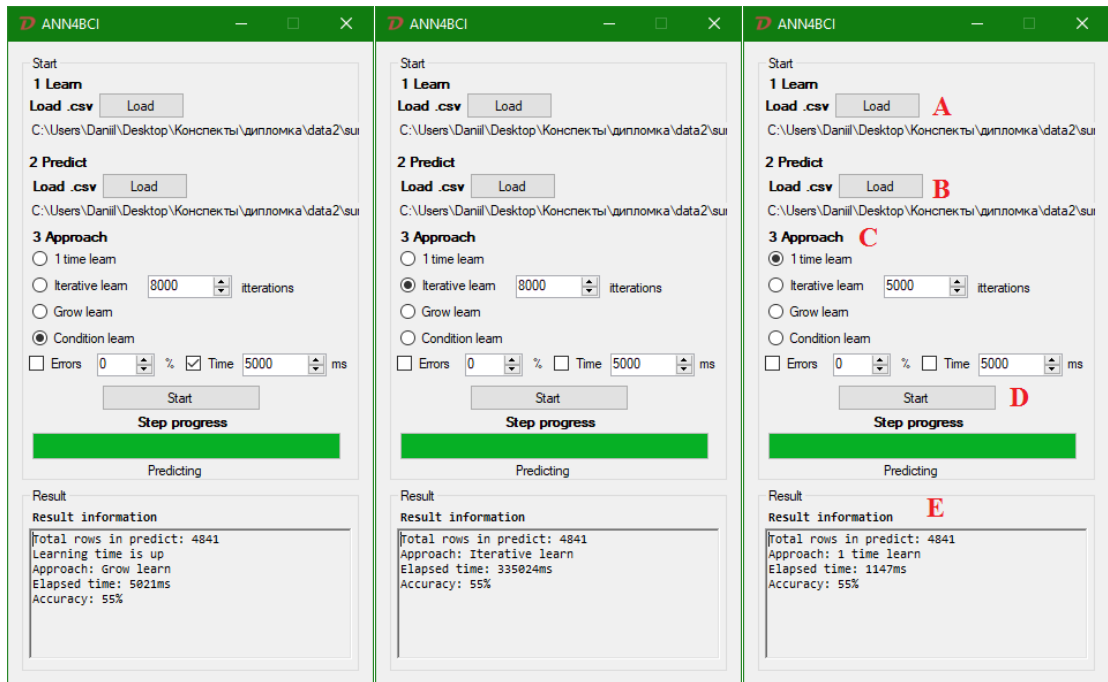
Figure 10. Demonstration of generated result from second series experiment's data

In Figure 9. the demonstration of ANN4BCI is presented. The ANN4BCI contains controls and other elements. The GUI is divided in two parts. In the first (Start Group box) part starting and configuration, there are only three buttons, two buttons are for loading the datasets

and one button to start. When the start button is clicked, ANN starts to learn. The software learns based on provided datasets. These datasets contain information about controller values such as checked or unchecked (0/1). One dataset is loaded for predicting without provided information about controller values such as checked or unchecked. So Accord.NET must predict and classify the brain state itself. The demonstration of the process is shown in Figures 9. and 10. The progress bar shows of progress of the current process and every process is labelled with a name.

The second (Result Group box) part of GUI shows the details about the loaded datasets. This part is used to show the total number of rows of loaded dataset for the prediction, elapsed time and shows the result accuracy of prediction. The loaded dataset will be predicted with controller values 0 or 1 based on the prediction and mark at the end of each row 0 or 1. The finally predicted dataset will be stored in a selected location.

In Figures 9. and 10., (A) allows the user to upload acquired datasets for learning and in Figures 9 and 10., (B) allows the user to upload acquired datasets for prediction. The datasets will be calculated and predicted without controller data (0/1). In Figure 9. and 10., (C) allows the user to select the approach of ANN.

- 1 time learn - ANN learns once and then immediately tries to calculate probability of the selected dataset. This approach is very fast, but the accuracy of the prediction is not good.
- Iterative learn - ANN learns based on user input and then tries to calculate based on the calculation. It predicts brain activity. This approach is much accurate than 1 time learning but it requires a bit more time to learn and predict.
- Grow learn - ANN learns based on acquired datasets row by row and when ANN moves to the next row it learns from the very beginning till the end of the current row and then move row by row. ANN keeps learning until it reaches the end of the dataset. It is an iterative process until it reaches the last row of the provided dataset. This approach simulates the live stream of the data flow. The speed of calculations in very high and accuracy increases with the increasing length of the dataset.
- Condition learn - ANN learns on all datasets till the conditions are met. The ANN4BCI allows setting two conditions: accuracy of calculations so the user must provide the percent to minimize the error. This is checked and calculated by built-in method of Accord.NET. The second condition is elapsed time. The software stops learning when

the time is up and the time is specified by the user. This approach takes a lot of time, but the accuracy of calculations is very high. This is more suitable for offline learning.

In Figure 9. and 10., (D) is a button which executes after the approach is selected to learn and predict based on provided datasets.

In Figure 9. and 10., (E) shows the result information such as: predicted size in rows, selected approach, elapsed time and accuracy.

5. DISCUSSION

The aim of this research study was to find an open source ANN for classifying EEG signals based on predefined parameters such as accuracy, execution time and system requirements.

Two series of experiments were conducted. 17 datasets were collected from 10 human subjects in the first series of experiments and 6 datasets were collected from 6 subjects in total in the second series. Experiments were conducted to collect the EEG signals for the classification of performance of ANN. A protocol was created for conducting the experiments and the protocol was explained to each subject before conducting the experiment. Mathematical and logical tasks were given to the subjects to stimulate the brain activity such as thinking and resting in first series of experiments and pictures and videos were shown in the second series of experiments to stimulate Motor-Imagery and observe the state of brain. The Bitronics helmet was used to acquire the EEG signals and BCIANNET version 2.0.0.1 to improve the classification based on ANN.

The acquired datasets were used to test the performance of five ANN based on the parameters such as speed of calculation, accuracy of classification and system requirements. Multiple ANN were tested in terms of performance of classification, namely Simbrain, Scikit Learn, Accord.NET, Shogun and Weka. The study shows that ANN from Accord.NET framework is the best for the classification among all ANN based on evaluated parameters. For Accord.NET, the speed of calculation was medium, accuracy was better (59.7% in thinking-resting tasks, 64% in MI tasks) and the system specifications were low.

Based on performance, finally Accord.NET was chosen to develop the BCI software which classifies, learns and predicts brain activity. The classified, learnt and predicted datasets are stored for further use.

Based on performance, finally Accord.NET ANN was chosen to update the BCIANNET version 2.0.0.1 software for classify the brain activity such as thinking or resting. The developed solution could be used to extend BCIANNET 2.0.0.1 so that BCIANNET will work in real-time environment. The developed BCI software could be used as a tool for the research in the bioelectrical field.

6. FUTURE WORK

The author will continue work to use this solution to extend BCIANNET 2.0.0.1 to make BCIANNET work in real-time environment.

This study covered aspects such as acquisition of the datasets from human subjects, evaluation of ANN and learning and predicting the state of brain activity such as thinking and resting. Nevertheless, research must move further in directions such as combining this study solution with BCIANNET 2.0.0.1, and to make a more robust solution not only classify two state of brain thinking and rest, but to classify all complex brain activities.

The outcome will be helpful for those people who are not able to use standardized input devices for some reasons. As a result, the final product will solve such problems.

ACKNOWLEDGEMENTS

APPENDIX A

The subjects get ready and get adjusted with the environment
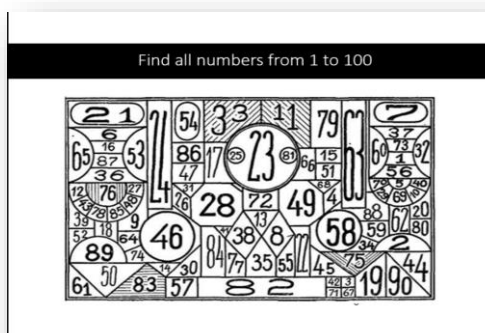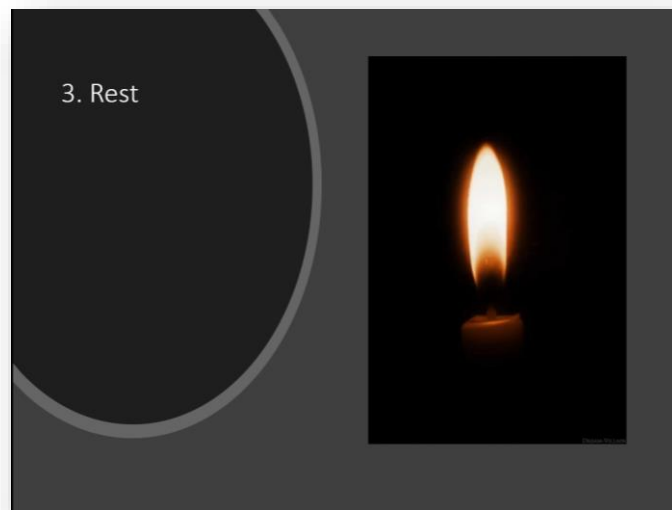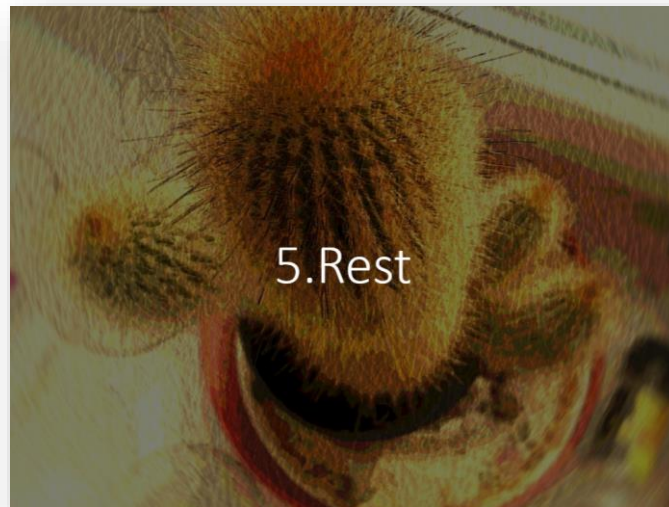
Task # 1

Task # 2

Task # 3

Task # 4

Task # 5

Task # 6
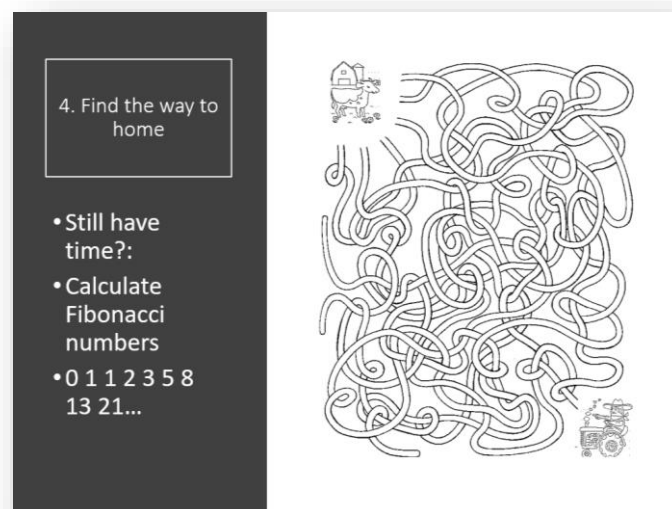
APPENDIX B

Task # 0

Task # 1

Task # 2

https://www.youtube.com/watch?v=4NUOjzbFj1g

Task # 3

Task # 4

https://www.youtube.com/watch?v=tXMPRK2LQAE

Task # 5

Task # 6

https://www.youtube.com/watch?v=-DPSfBeMDm8

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