Comparison of Active and Passive Attention Based Tasks Using EEG Waves with Convolutional Neural Network

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Abstract— **A person's state of attentiveness can be affected by various outside factors. Having energy, feeling tired, or even simply being distracted all play a role in someone's level of attention. The task at hand can potentially affect the person's attention or concentration level as well. In terms of students who take online courses, constantly watching lectures and conducting these courses solely online can invite in lack of concentration or attention. Tasks can be divided into two categories: passive or active. Conducting active and passive attention-based trials will reveal varying results in different states of attentiveness. This paper compares active and passive attention trial results in two states, wide awake and tired. This has been done in order to uncover a difference in results between the two in the different states. The data analyzed throughout this paper was collected from electroencephalogram (EEG) waves, and later processed through a 3D Convolutional Neural Network (CNN) to produce results. Three passive attention trials and three active attention trials were performed on seven subjects, while they were wide awake and again when they were tired. Experiments conducted in this study were ran on both raw and preprocessed data. The preprocessed data experiments resulted in accuracies as high as 81.78% for passive validation accuracy and 63.67% for active validation accuracy.**

Keywords—component: Active attention, classification, electroencephalogram (EEG) waves, passive attention, and preprocessing.

I. Introduction

Concentration levels are affected by various outside factors. A person's state of attentiveness and the task at hand are just some of the factors that can affect their concentration. In terms of students who take online courses, constantly watching lectures and conducting these courses solely online can invite in lack of concentration or attention. Attention, specifically in educational environments, has been studied to reveal mechanisms that increase a student's attention and concentration. With the help of electroencephalogram (EEG), brain signals can be detected and recorded in order to analyze areas like a person's attention level. EEG provides an effective and efficient way for researchers to collect brain data for studies and further analysis.

EEG has been used to study brain disorders [1], look at the attention levels of students [2], and assess a subject's mental workload [3]. Attention specific research in conjunction with EEG has also been conducted within recent studies. One way this research has been further developed was through the classification of attention using EEG. In [2], a protocol was developed in order to be able to classify human attention into states of attention and non-attention. This study resulted in classification accuracies as high as 92.8% and 92.4% [2]. Similarly, [4 – 6] observed student attentiveness in order to determine if students are actually attentive during class and resulted in classifications of attentive or inattentive. The study conducted in [4] found that when looking at attentive vs. inattentive, attentiveness is easier to classify and detect than inattentiveness. Focusing specifically on students and attention levels, [6] discovered a positive correlation that revealed students who participated more had a higher attention level. Another way attention and EEG research has been developed involves using convolutional neural networks to assess mental workload (active) tasks [3, 7]. These studies proposed the use of neural networks to allow for mental workload assessment classifications.

A review of previous experiments uncovered a gap in the study of attention/concentration, EEG, and neural networks. The results of mental workload assessments have never been compared to results of passive attention assessments or tasks when considering two states of attentiveness: wide awake and tired.

Passive attention tasks do not require any real physical or mental work. On the contrary, active attention tasks are thought provoking, which require some level of mental and physical work. With that being said, a test subject is more likely to lose concentration during a passive attention trial, when tired, than they are wide wake. It is more common for the same subject to perform similar during active attention trials, wide wake or tired, because of the level of concentration that is required to perform the task.

When considering a student's attentiveness while taking online courses, it is known that they tend to lose focus or get distracted at some point during the lecture. It is said that humans are supposed to learn in active environments [8]. Watching a lecture from a screen is considered a passive task. Combining that with another factor, like fatigue, decreases attention even more. Keeping students in mind, this paper was developed in order to ultimately help students in online courses maintain a high level of attention. Positive results should encourage students to take breaks during passive tasks or even completely stop and return to it another day in order to produce optimal results on their studies.

The main contribution of this paper proposes a comparison of active and passive tasks at different levels of concentration: wide awake and tired. This paper will analyze

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different datasets from active attention-based tasks (also referred to as "mental workload tasks") and passive attention-based tasks ("attention tasks"). During data processing, functions of frequency analysis and time analysis will be applied and compared. Frequency analysis is achieved through the implementation of Fourier transformation. On the other hand, time analysis is performed simply by processing the data without including Fourier. Both of these analyses will also be combined through implementing Wigner Ville Transformation/Distribution (WVD) into the 3DCNN. In addition to frequency and time analysis, experiments consisting of selecting specific sensor channels from the data will be performed. The experiments discussed previously will be applied to the data in order to extend our research. A comparison of the EEG waves, produced by performing mental workload and attention tasks, will uncover a difference between the results of the two types of tasks while wide awake and tired.

First, both active and passive attention-based trials will be held to gather data. The active attention trial will be held while a subject is wide awake and again when the subject is tired. The same will be done for the passive attention trials. We will then use a 3DCNN to process and categorize the data. The data categories include: Active-Sleepy, Active-Awake, Passive-Sleepy, and Passive-Awake. All categories will be compared to each other for various reasons. The first reason is to ensure that classification is accurate. The comparisons are also performed to reveal a difference between the active and passive results at the different attention levels. We propose that the results of the active attention trials will remain stable, whether the subject is wide awake or tired, whereas the passive attention trial results will have a noticeable difference.

The following sections outline the remainder of this paper: first, the methods used to conduct this research, such as signal processing and data collection are discussed. The next section describes six different experiments performed on datasets ranging from raw data to preprocessed data. Section IV provides an explanation of the results achieved from using Machine Learning to process EEG data waves. Lastly, the conclusion closes out the paper.

II. Methods

A. Motivation

The original focus for this project was to create a 3DCNN that could accurately identify the source of EEG signals and relate them to various moods and stimuli. Under this project direction, subjects were exposed to two additional videos, a scene from an action movie, and a recording of a ballet class. Subjects were also tasked to write a short sentence about the videos, without any direction as to what to write about. These tests were to be analyzed by a 3DCNN and provide information, not only on the reaction of the subjects, but also the possible identity of the subjects. For example, a subject who studies ballet may have more activity in the Beta frequency because they are analyzing the technique of the performers in the video as they would analyze themselves. A technology student may have more activity in the Beta frequency during the programming video because they are analyzing the program in front of them in as they would in a classroom setting.

Once the project shifted to focus on the attention aspect of subjects, the data collection plan morphed to focus on activities that would test a broader range of responses from the brain. Specifically, the project called for varying levels of difficulty in a range of tasks in order to gauge the attention level required for such tasks. The development of the 3DCNN became more focused on accurate classification of already classified datasets. The development also became more independent, as the previous study had algorithms like MUSIC and sLORETA to guide the process.

The chosen method of testing the hypothesis for this project begins with the data collection. The data collection plan, as shown in Figure 24, consists of the following, each lasting for a duration of thirty seconds:

- A recording of mouse movement on a blank document
- An excerpt of Embraceable You by Sarah Vaughn
- An instructional video on creating functions in Python
- Three computer games that challenge memory, mathematical computation, and visual identification

The purpose of using the three computer games challenging various skills is to put stress on the subject's mental workload, which is "the amount of mental or cognitive resources required to meet the current task demands" [9]. Conducting tests that promote mental activity is also supported by [10], in which a study of ten subjects performing mathematical equations demonstrated that mental or motor activity spurs an alpha-blocking phenomenon. This study further validates the usefulness of EEG testing when attempting to analyze brain activity.

Since the hypothesis requires data from subjects when they are awake and tired, a method of converting an originally awake subject to a tired subject had to be created. This was commonly done by taking feedback from the subject as to what typically puts them in a tired state. Subjects usually watched videos of a person explaining a concept in detail or of a static background image with calming music. The environment in which the data collection occurred was changed by dimming the lights and closing the blinds.

B. Signal Processing

An EEG signal is a measurement of currents that flow during synaptic excitations of dendrites. When brain cells are activated, synaptic currents are produced within dendrites. These currents generate a magnetic field measurable by EEG devices that use metal electrodes to record the electrical signals. EEG recording devices are advantageous to projects like these because they are non-invasive, low cost, and provide real-time feedback [11]. A similar study uses EEG to measure the effects of mental stress [12, 7], validating the use of EEG for this project, as well. One of the limits to collecting EEG data include a low signal to noise ratio due to the number of external sources that interfere with the measurement of brain activity [13]. This makes it hard for brain-computer interface (BCI) systems to conduct feature extraction and pattern recognition internally [11]. Another issue is that the signals are not static over time by nature. Thus, generalization techniques based on time-frequency methods may inaccurately generalize data from the same subject during a different epoch [13]. The signals are measured in hertz and are classified in the following manner [14]:

- Delta – Delta waves occur at 0.5 – 4 Hz. These signals typically occur during deep sleep but can also be present in waking. Artefact signals caused by large muscles of neck and jaw can be confused with these, because those muscles are close to the skin.
- Theta – Theta waves are typically recorded at 4-7.5 Hz. These signals usually occur as a subject is slipping from consciousness to drowsiness.
- Alpha – Alpha waves are typically recorded in 8-12 Hz. These signals are found at the posterior of head, over occipital region. They usually occur during relaxed awareness without attention or concentration. Most subjects produce some alpha waves with eyes closed.
- Beta – Beta waves occur at 14-26 Hz and are found in the frontal and central regions of the brain. They are related to active thinking, attention, and solving concrete problems. They are commonly found normal in adults. High levels of beta waves are related to a state of panic. These signals can be blocked by motor activity or tactile stimulation.
- Gamma – Gamma waves are greater than 30 Hz and found in the frontocentral area of the brain. These signals are rare. Gamma waves can be used to demonstrate locus for right and left index finger movement, right toes, and tongue moments.

The following image depicts the typically style of an EEG recording device, which includes the DSI-24 that was used for this project.

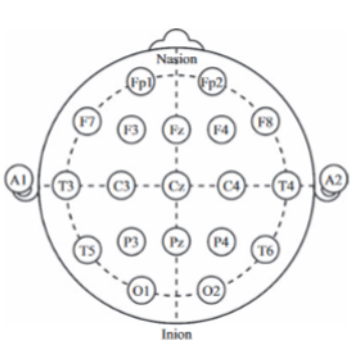

Fig. 1 – Diagram of EEG head model.

As the device records data, it is imperative that subjects remain still and try not to blink. Auxiliary movements such as these create artifacts in the data [15] that affect post analysis of the signals. These artifacts should be removed from the data through preprocessing before the data is used in an analytical capacity.

1) Data Preprocessing

Signal preprocessing is the preparation of signal data for analysis. This step is controversial in importance. It is believed that preprocessing data is crucial for "achieving high classification accuracy" [7]. It has also been reported that a substantial amount of preprocessing is required for experiments that assess cognitive workload [13]. However, recent studies that use raw EEG data have found much better performance that their counterparts using preprocessed data [13]. This project has been able to train the model and run tests with both, noticing a major difference in performance between tests with preprocessed data and tests with raw data. The following techniques are often used to achieve clean data:

a) Denoising

When collecting EEG data, there are a variety of variables that affect the signal. According to [7], it is crucial that EEG features are removed from data. This includes events like eye blinks, ECGs, and EOGs. For EEG signal recording specifically, blinking artifacts are a significant problem area [16]. Eye blinks are one of the most disruptive signal events to occur in EEG recordings, as found in a study on the sensitivity of EEG results from preprocessing methods [17]. The LARG approach to ICA is developed to remove blink artifacts, however its amplitude ratio of less than one creates the concern that "too much EEG signal has been removed" [17]. Blink artifacts can also become indistinguishable from regular data when evaluated by epochs [17]. Most noise is generated within the brain or over the scalp; Only large pops of active neurons can generate enough potential to be recordable using scalp electrodes, thus signals are amplified for display purposes. Through the process of denoising, the modulation of signal information by these events can be mitigated.

b) Filtering

Filtering is a significant tool for preprocessing data because it allows interfering events to be easily identified and separated from the data points of actual interest. There are two types of filtering: adaptive and nonadaptive. Adaptive noise cancellers require a quality reference signal. For example, to cancel out noise created by eye blinks, strong data must be collected that reflects the signals from eye blinks by the subject. This data can then be used as a reference for the noise canceller.

A basic filter for EEG data is a low pass filter of about 50-70 Hz and a high pass filter less than or equal to 0.5 Hz. High-pass filtering is beneficial for removing EOG's because they typically occur at low frequencies [11]. Similar studies use a high pass filter of 1 Hz [18, 9], as recommended by EEGLAB. Despite this recommendation, the high pass filter remained at 0.5 Hz as high pass filters of more than 0.05 Hz have been cited as resulting in distorted data [19]. Similar studies also used a filter of 0.5-49 Hz for noise reduction [2, 7]. The following is an image of the configuration options provided for applying filters to imported data sets:

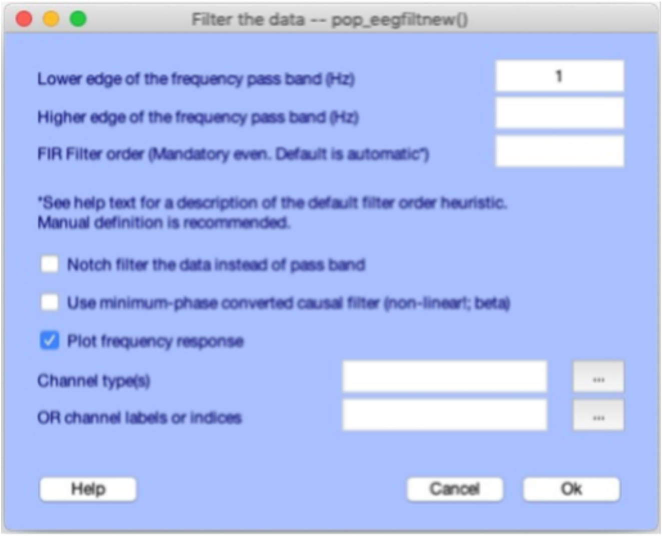

Fig. 2 – Configuration settings for preprocessing filter.

c) Feature extraction

Feature extraction is the classification and removal of informative features from the dataset. The features that can be removed are temporal, frequency domain, and time-frequency features. For temporal feature extractions, the methods used include amplifying raw EEG signals, autoregressive parameters, and Hjorth parameters. Frequency domain feature extraction methods include signal filtering and synchronization. Time-frequency feature extraction methods are based on the short-time Fourier transform and are helpful in catching "sudden temporal variations of the signals…" [20]

d) Re-referencing

Re-referencing is a form of preprocessing that is used specifically for EEG data by averaging the signals from opposite nodes. This method is used to counteract the appearance of asymmetric spatial distribution with signals that are symmetric.

The main idea of re-referencing is that when the reference nodes are added together, they result in 0. This is based on Ohm's law and is attributed to the idea that for a positive current from the electrical source, there is a responding negative current [21]. For EEG data collection electrodes, the nodes that are most used to create this optimal average reference include Cz, TP10, or earlobe links.

The limitations for re-referencing occur when the distribution of electrodes is considered. Accurate average reverence data requires that the electrodes are placed at a fixed, equal distance across the head surface. This is not always the case during data collection. Specifically, during this project, the electrodes had to be manipulated in a non-linear pattern to ensure that an accurate signal could be achieved.

C. Deep Learning

The core of this project is the ability of the 3DCNN to accurately identify the data sets according to the state of consciousness of the subjects and whether the task they were performing was active or passive. Deep learning is a form of representation learning, which is "a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification." [22] What separates deep learning from other machine learning methods is the use of layered modules that create a neural network, which are networks comprised of more than three layers, including an input and output layer. As data passes through these layers, the deep learning algorithm creates a low-level representation of how to approach the given data by extracting high-level and low-level features necessary to perform classification [23]. Each layer consists of nodes that respond to data based on its passage through the input layer and the threshold of the node itself.

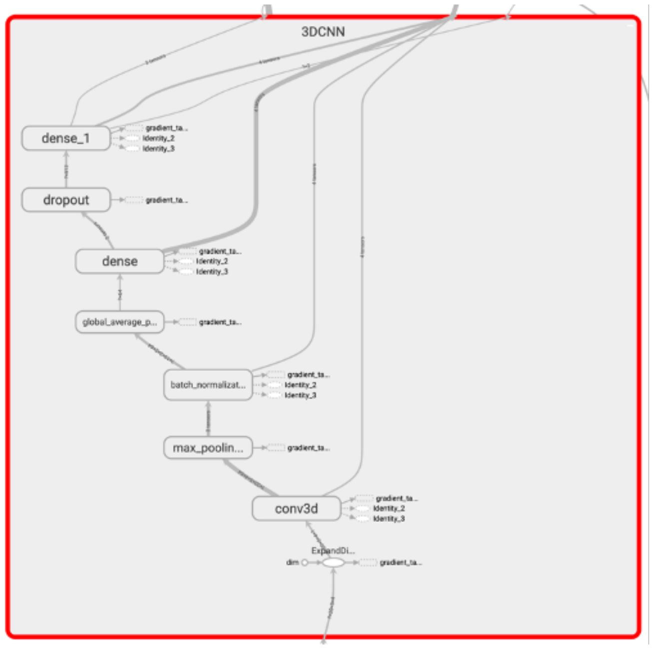

Fig. 3 – 3DCNN Model.

For this project, the 3DCNN consisted of six intermediate layers and one output layer:

1) 3D convolution (64 filters, input kernel size, ReLU)
2) 3D max pooling
3) Batch normalization
4) 3D global average pooling
5) 512-unit Dense (ReLU)
6) Dropout (0.3)
7) Output layer: Dense (Sigmoid).

Layers can go from four to thirty-two in number; However, it has been found that EEG data is best reviewed in deep learning algorithms with shallow neural networks [13]. The neural network used in this project is a convolutional neural network (CNN). In [7], it is noted that CNN's perform better that "state-of-the-art methods" of feature learning. CNN's are used "to process data that come in the form of multiple arrays" [22]. They first few layers of CNN's are comprised of a convolutional layer and a pooling layer. The next layer is typically an ReLU, followed by additional convolutional and pooling layers. [22] Deep learning can also be used during the preprocessing process by implementing preprocessing techniques, feature extraction, and classification during the training process [13]. However, the lack of architectures and practices surrounding preprocessing for EEG data specifically through deep learning make this usage unpopular [13]. For this project, the 3DCNN performs classification on its own, receiving previously preprocessed data exported from the EEGLAB module. Because this project focuses on inter-study classification, the model must contend with greater data variability. In an intra-subject focused project, an accurate model is created based on a specific subject but faces a challenge when introduced to new subject data [13]. Deep learning algorithms related to EEG data typically perform best when they are trained on a variety of subjects, then fine-tuned to classify information for a specific subject [13]. Though the general scope of this study is to find an overarching difference in performing active and passive tasks under different levels of consciousness, the findings from this study would be best fit when applied to a singular subject after the initial training on multiple subjects.

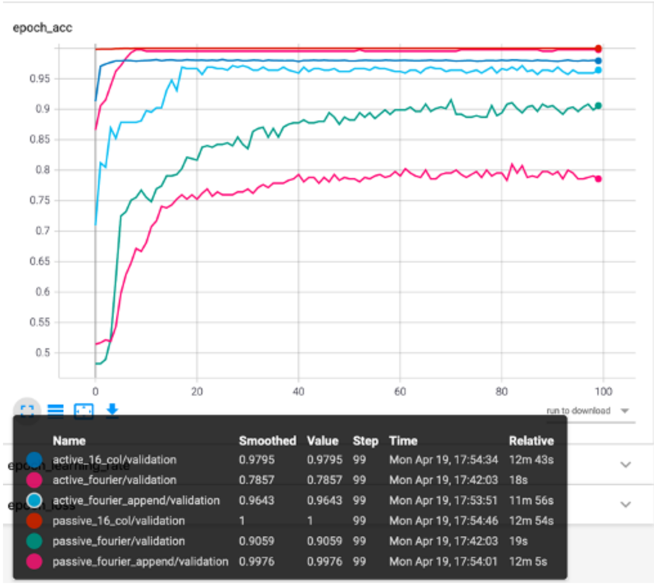

Fig. 4 – Unprocessed Validation Accuracy During Training.

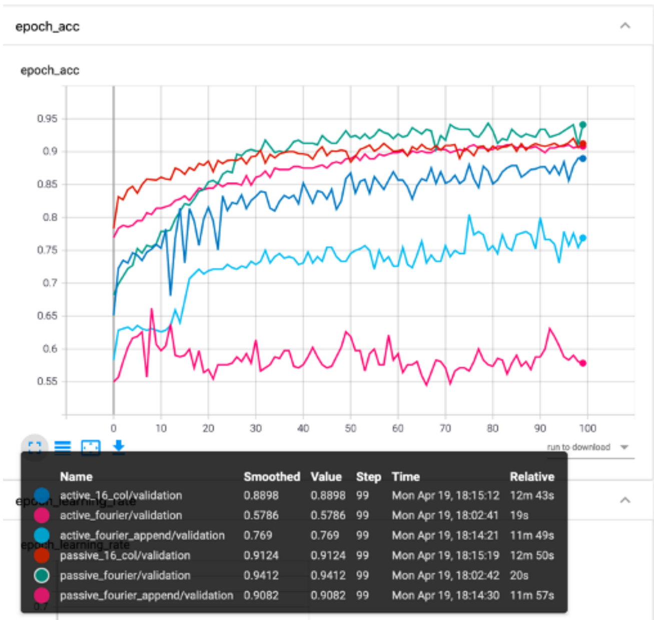

Fig. 5 - Preprocessed Validation Accuracy During Training.

D. Data Collection

The data was collected and separated through the nomenclature of the files. While collecting data, it was also imperative that the environment be controlled to supply the best possible data for preprocessing and analysis by the 3DCNN. In experiments like these, there are four main sources of artifacts: the EEG equipment, the electrical interference external to the patient and the recording system, the leads and the electrodes, and the subject themself [24]. EEG's can pick up artifacts like alternative current artifacts, electrode artifacts, movements in recording environment, and interference from other equipment [11]. Alternative current artifacts are artifacts that occur above 60 Hz and are caused by insufficient installation of the EEG device onto the subject's head. If the electrodes are not seated properly on the scalp, "the impendence between the ground of the amplifier and the active electrodes of the EEG becomes considerably large" [11]. Electrode artifacts occur when electrodes are not positioned in the correct place on the subject's head. These two are the largest causes of artifacts in the data for this project as most of the subjects had hair that impeded the ability to properly position the DSI-24 on their scalps.

E. Equipment

To collect the data, an EEG sensing device called the DSI-24 was used along with recording software provided by Wearable Sensing. The device has 21 electrodes and provides coverage from the forehead to just above the nape of the neck. Although devices with more electrodes are available, the advantages for using a low-density EEG are a short setup time, lowered risk of nonbiological artifacts, and lower impedance from neighboring electrodes [25]. Another advantage of using the DSI-24 was cleanliness of the equipment. Other EEG testing devices require the use of gel to create conductivity between the sensors and the subject's head. As most subjects for this project had long or thick hair, a device that required gel application would have hindered the ability to conduct the current amount of experiment. The computer interface also allowed the brain activity recordings to be exported into EDF and CSV file types. The EDF file types were necessary for preprocessing through the EEGLAB module.

Preprocessing was performed in Matlab R2018a, using the EEGLAB module, which is a popular module for a variety of studies using EEG data [18, 9]. All subject data was anonymized by using a number, instead of the subjects' names as the classifier for the data.

III. Experiments

Experiments were conducted on seven subjects. Subject were non-linear in identity and belong in the age range from 18-22 years old. A similar study pointed out that variations in gender and educational background could affect the outcome of the data. For example, "female skulls have light skull structures" which can result in a stronger signal for female subjects, when compared to male subjects [9]. Each of the subject's voluntarily agreed to participate and provided a signature as written consent. Recruitment for the study was done through oral transmission. The details of the experiment were explained to each subject before beginning and subjects were frequently asked to provide verbal feedback on their comfort level. Subjects completed all tasks in a seat position, about 2-3 feet away from the device displaying the stimulation material. The full data collection plan was followed with each subject under two separate states of mind: once as they were alert, and once again when they reported that they felt tired. The state of a subjects' consciousness during recording is subjective as it was self-reported.

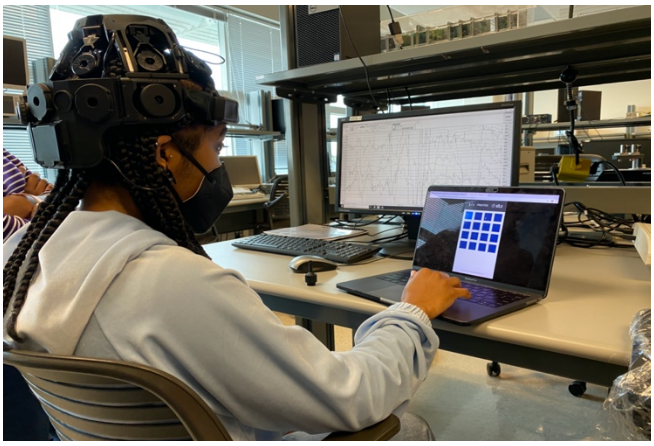

Fig. 6 – A subject conducting an active attention-based trial.

A. *Freely Available Data Sets*

The developers of EEG lab provided free data sets to be used for training the machine learning aspect of the project. These data sets were used for preliminary testing of the 3DCNN to ensure that the model would be able to work as intended for the datasets specific to the project.

B. *Raw Datasets*

After fitting the DSI-24 on the subjects' head, small adjustments were made to the electrodes to obtain a strong signal from the software. The signal was considered acceptable once the visual mappings of the sensors were yellow or green in color. For all tests, subjects were given a brief and general description of what they would see, hear, or interact with. Each test required minimal movement and was taken while the subject was seated and with their head in one position. All tests were recorded for approximately thirty seconds.

The first passive test required the subject to watch a video of a mouse cursor moving over a blank document and follow the movement with their eyes. The second passive test required subjects to close their eyes and listen to a 30-second excerpt of Embraceable You by Sarah Vaughn, a jazz song originally recorded in 1954. The last passive test required subjects to watch a 30-second excerpt of a video in which a woman explains how a function works and how to create a basic one using Python.

The first active test required subjects to play the 2048 game on an online gaming website. The game consists of a 4x4 grid and starts with two blocks holding the number "2". The goal is to use the arrow keys to push the numbers together and ultimately create a block holding "2048". The blocks will only combine if they are the same number. The subject will lose if the entire 4x4 block grid is filled. The purpose of this game is to challenge subjects on the arithmetic and strategy skills.

The second active test requires subjects to play an iSpy game. The subject is provided with an image of assorted objects. A clickable list of objects that are both present and absent is located directly beneath the picture. The goal of the game is to click on the object in the list once the subject can identify it in the picture. They are given 30 seconds to identify as many objects as possible. This test challenges one's visual identification and reaction skills.

The final active test requires subjects to play a memory game. The game provides a 4x4 block grid of blue tiles. The tiles will turn light blue in a specific sequence. The subject must then click on the tiles in the exact sequence to move onto the next level. The sequences become longer as the subject advances through them. This game challenges the subject's memory. Much like [12/13], the first and last test have an increase in difficulty embedded in the test in order to increase mental stress.

C. *Preprocessed Datasets*

Processing applied to preprocessed datasets include filtering, denoising, bad channel removal, and independent component analysis (ICA). Some preprocessing methods were not possible to achieve through EEGLAB due to missing channel location data for the DSI-24.

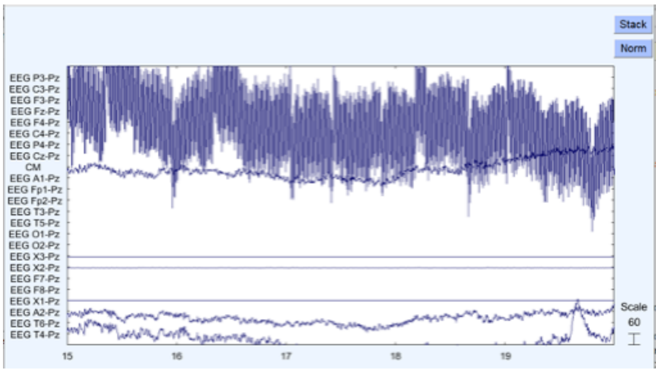

Fig. 7 – Depiction of raw data from subject 5.

All data was passed through a preprocessing script, shown in Figure 25. A high pass filter of 0.5 Hz and low pass filter of 50 Hz applied using *pop_eegfiltnew()*.

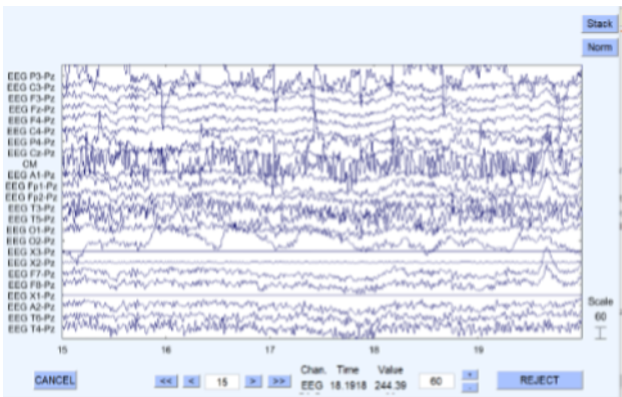

Fig. 8 – Data for subject 5 after running filter with pop_eegfiltnew().

Using *pop_select()*, the script removes channels X1, X2, and X3 as these nodes were not used during the data collection process.

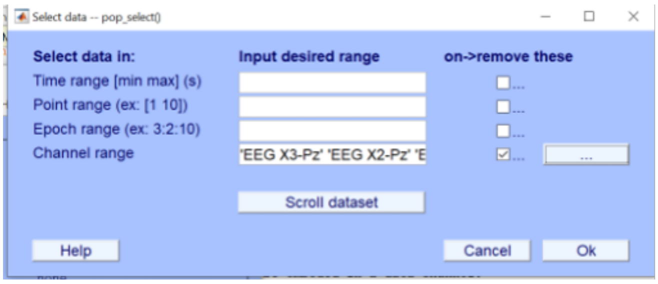

Fig. 9 – configuration settings for isolating or removing bad channels

The script then removes excerpts of the data that seem to be outliers based on an averaging of data by using *pop_clean_rawdata()*. This method employs Artifact Subspace Reconstruction (ASR), which removes large-amplitude artifacts [9]. There is a clear difference in the data between Fig. 7 and Fig. 8 as the data is run through various filters. [9] found an increase in the accuracy of the data after running ASR.

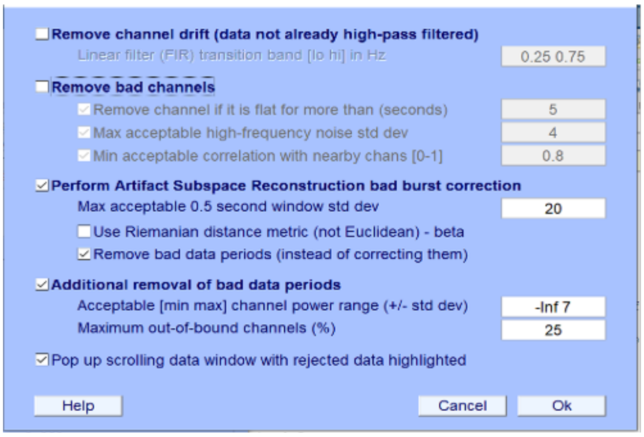

Fig. 10 – Configuration settings for ASR and removal of bad channels.

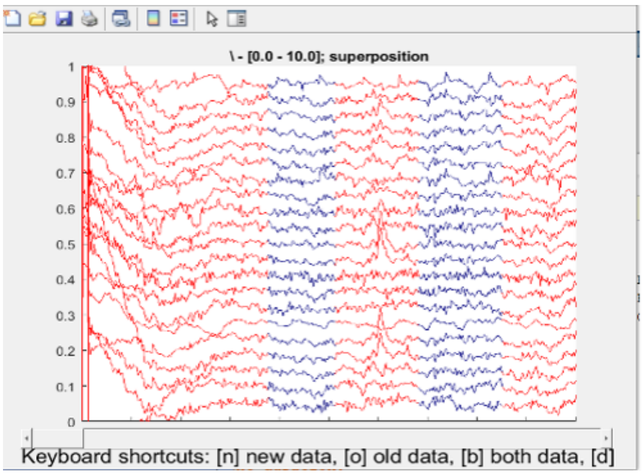

Fig. 11 – Depiction of data after running pop_clean_rawdata(); Red = removed data; Blue = remaining data.

Finally, the script performs decomposition by ICA using *pop_runica()*. The purpose of running ICA after bad data has already been removed is to remove any events that have been missed. This decision is backed by the results of [17]. Authors of [17] recommend that "researchers generally assume residual blink signals are present in their data after preprocessing and take active measures to address this when interpreting their results".

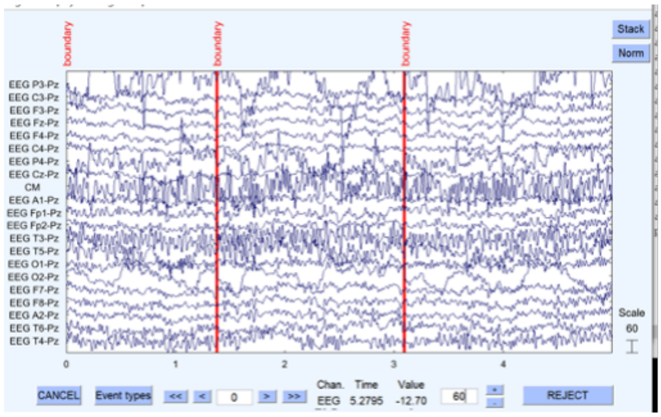

Fig. 12 – Depiction of data after running pop_runica().

Preprocessed datasets were then exported and formatted into CSV files for interpretation by the 3DCNN.

Preprocessing through EEGLab did not increase accuracy for machine learning. The results discussed in later sections are based on a secondary attempt to preprocess data through the MNE-Python package. These preprocessing efforts were focused on averaging the data, as opposed to legitimizing the data. The script for this method displays the creation of baseline, a standard filter of 0.5 - 50hz, referencing to the common mode, then removing auxiliary channels and the common mode (Figure 13).

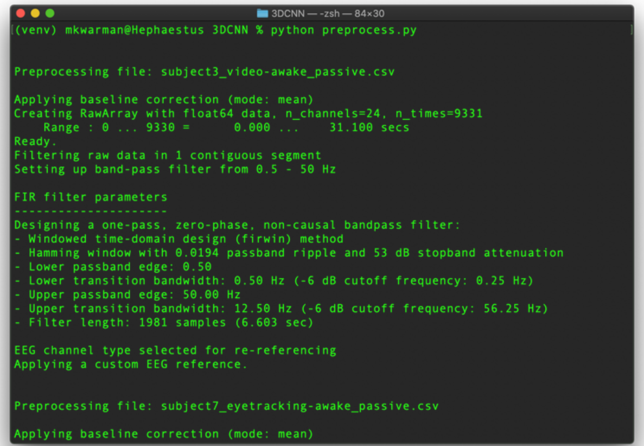

Fig. 13 – (MNE-Python) Depiction of Preprocessing in Progress.

The image in Figure 14 represents data before preprocessing, and the image in Figure 15 represents the data after preprocessing using a data-averaging approach.

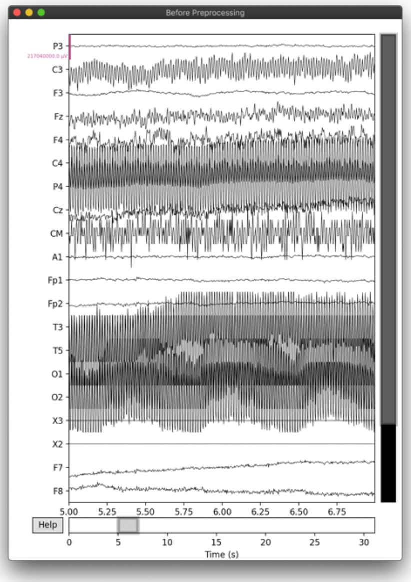

Fig. 14 – (MNE-Python) Data Before Preprocessing.

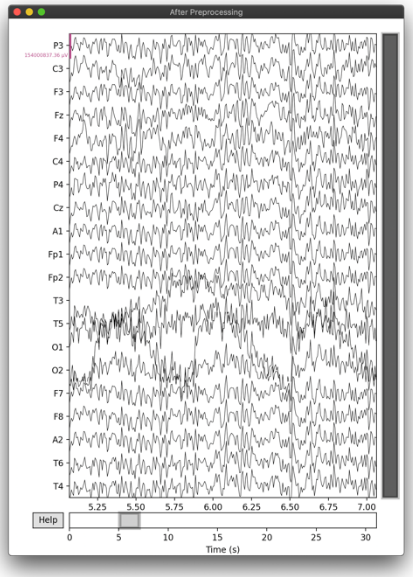

Fig. 15 – (MNE-Python) Data After Preprocessing.

Both approaches resulted in cleaner, more distinct signals. However, the 3DCNN responded with much higher accuracy towards the averaging approach. The 3DCNN may have been able to achieve better accuracy through a data averaging approach because the system is allowed to view the entire spectrum of brain activity. In an approach that consists of removing pieces of data, the model can miss epochs of data that would otherwise contribute to the learning process.

D. *Comparison of Active and Passive Datasets*

Preprocessed data sets were then loaded into the TensorFlow model to train the model specifically for the collected data. The results of the model training are saved in an instance of a Python class called *ClassificationContext.* This object can then be easily used to gain insights and compare results. The object has four noteworthy functions:

- *make_predictions()* - This function will iterate through a given number of validation rows and return how confident the model is that a given label is the correct match for the data, and what the actual label for that data is. This function was used during early development of the model to see where the model excelled and where it struggled. The data label prediction certainties do not sum to 100%. Each label is assigned its own confidence percentage.
- *check_predictions()* - This function will iterate through a given number of validation rows and check if the model's prediction is correct. By default, only incorrect predictions are returned. This function was used during early development of the model to see where the model excelled and where it struggled.
- *get_average_prediction_error()* - This function iterates through every validation data group, checking for how confident the model is in its results. The interval between the 'correct' certainty of a label match (0% or 100%) and the actual model result is averaged for every label of every validation data group and returned. For example, if for a given validation data group, the model is 20% certain that the matching label is "awake_active" and 80% certain that the matching label is "awake_passive", the average prediction error for that validation data group is 0.2 (20%). The data label prediction certainties do not sum to 100%, each label is assigned its own confidence percentage. This function was used for our final analysis.
- *get_accuracy()* - This function returns the accuracies of the trained model when training data is input and when validation data is input. This function was used for our final analysis.

IV. Results

There were a total of eight different experiments performed on both raw and preprocessed data. The results explained below were retrieved from the following experiments: Active Sleepy vs Active Awake, Passive Sleepy vs Passive Awake, and Comparison of Active vs Passive.

A. *Raw Data Results*

To start off, experiments were first performed on raw unprocessed data. Throughout the process of model development, over one hundred tests were conducted on the raw data. These tests included reducing the number of sensor channels, selecting nodes from specific regions on the headset, expanding the Fourier transformation bands, and implementing the Wigner Ville Transformation/Distribution (WVD).

When reducing the sensor channels, tests went from using 20 nodes to 16, 12, 9, 6, 4, all the way down to only 3 nodes. The nodes used in these experiments were chosen randomly. After testing all of these different sensor channel ranges, we found that the using 16 nodes produced the highest accuracy from our model: 97.75% Active Validation

Accuracy and 100% Passive Validation Accuracy. These were some of the highest accuracies seen among all tests. The lowest Active accuracy percent came from only using four nodes, while the lowest Passive accuracy occurred with three nodes. See Fig. 16 for additional results.

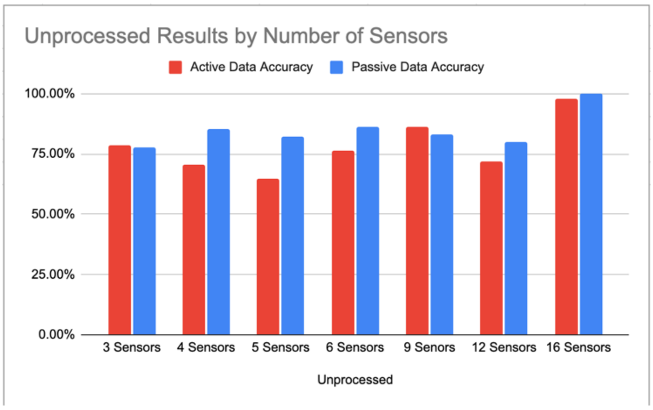

Fig. 16 – Raw Data Results by Number of Sensors.

Other tests included choosing nodes from specific regions, like the front, back, left, and right areas of the headset. For these experiments, groups of two and four nodes from each section were chosen and ran through the model. Amongst these experiments, the highest accuracy came from intentionally using two nodes from the front area. These percentages include 80.49% Active Validation Accuracy and 81.35% Passive Validation Accuracy.

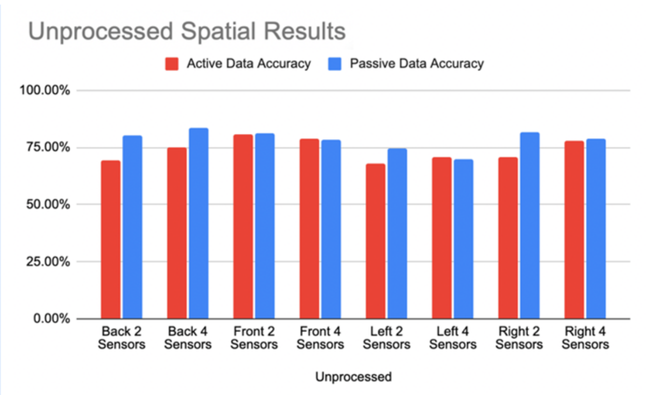

Fig. 17 – Raw Data Spatial Results.

Experiments that involved the expansion of Fourier transformation bands, started with only five bands and expanded all the way to 110 bands. The results of five bands display percentages of 78.33% Active Validation Accuracy and 89.18 % Passive Validation Accuracy. When expanded all the way to 110 bands, the accuracy began to decrease: 77.14% Active Validation Accuracy and 80.71% Passive Validation Accuracy. See Fig. 18 for more results.

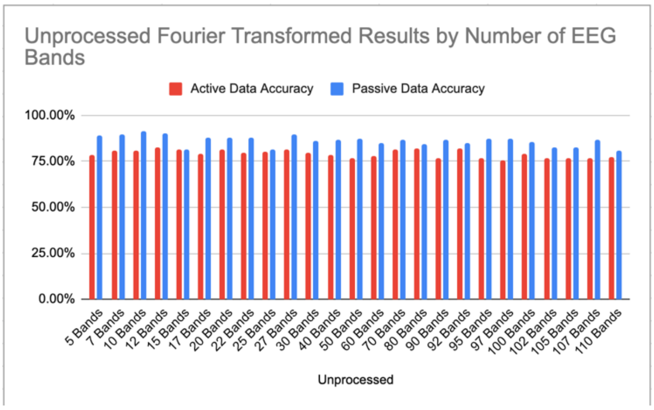

Fig. 18 – Raw Data Fourier Transformation Results.

The last experiment conducted on the raw data involved implementation of the Wigner Ville Transformation/Distribution (WVD). This transformation was implemented in order to see if it produced more accurate results than the Fourier transformation. With only five bands, WVD had a percentage of 56.96% Active Validation Accuracy and 56.99 % Passive Validation Accuracy. Compared to the tests ran on Fourier transformation with five bands, discussed before, WVD is more accurate than Fourier transformation. The WVD results can be seen in the "Time-Frequency" section of the graph in Fig. 19.

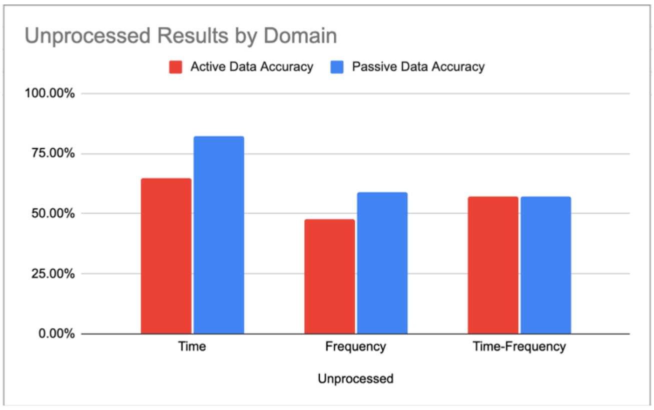

Fig. 19 – Raw Data Domain Results.

Averages of all these tests combined resulted in 79.37% Active Validation Accuracy and 84.61% Passive Validation Accuracy. In terms of training data accuracy, the model was 4.64% more accurate when differentiating between passive sleepy vs passive awake than it was when trying to do the same for active sleepy vs active awake. At the same time with validation data, the model was 5.23% more accurate when differentiating between passive data in the two states than active data. This data supports the initial prediction made in our proposal.

B. Preprocessed Data Results

The preprocessed data was tested after all raw data experiments were performed. Preprocessed data experiments covered the same areas as raw data. To reiterate, these experiments included reducing the number of sensor channels, selecting nodes from specific regions on the headset, expanding the Fourier transformation bands, and implementing the Wigner Ville Transformation/Distribution (WVD).

Reducing the number of sensor channels provided similar results in both raw and preprocessed data. Like the raw data results, preprocessed data performed the best with the use of 16 nodes. The percentages for 16 sensor channels were 80.15% Active Validation Accuracy and 88.42% Passive Validation Accuracy. For additional results, refer to Fig. 20.

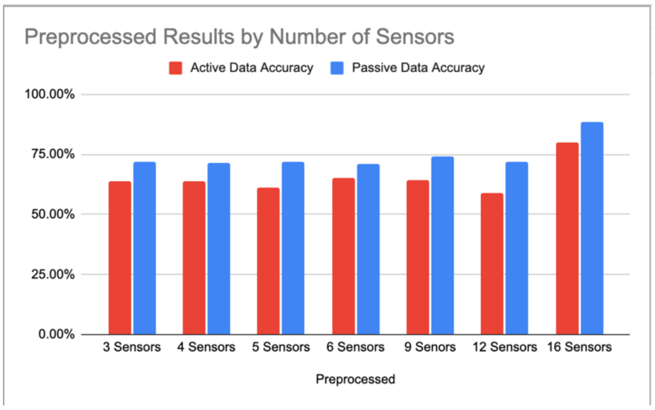

Fig. 20 – Preprocessed Data Results by Number of Sensors.

When examining the results from choosing specific regions, all the areas produced very similar results, but the overall highest accuracy came from using two nodes in the back. The percentages included 62.97% Active Validation Accuracy and 74.88% Passive Validation Accuracy. Again, the outcome from these experiments were close, so see Fig. 21 for details on the additional results.

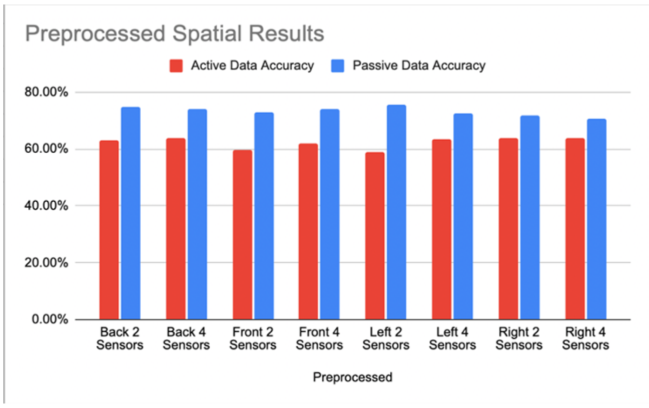

Fig. 21 – Preprocessed Spatial Results.

Expanding the Fourier transformation from five bands to 110 bands resulted in accuracies that fluctuated between increasing and decreasing. Unlike the raw data results, there was no steady decrease in accuracy for the preprocessed data. Five bands resulted in 57.86% Active Validation Accuracy and 94.35% Passive Validation Accuracy, while 110 bands produced accuracies of 59.52% Active Validation Accuracy and 96.47% Passive Validation Accuracy. See Fig. 22.

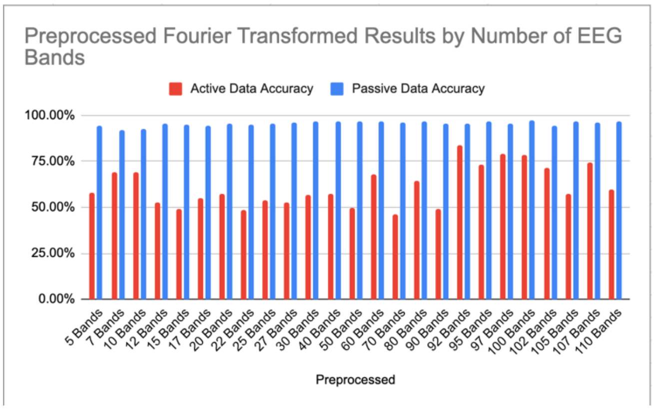

Fig. 22– Preprocessed Data Fourier Transformation Results.

One of the lowest accuracies came from the experiment with WVD. The WVD with five bands displayed accuracies of 56.48% Active Validation Accuracy and 68.63% Passive Validation Accuracy. Compared to the Fourier transformation with five bands, WVD produced more accurate results. The results of WVD can be seen in the "Time-Frequency" section of the graph in Fig. 23.

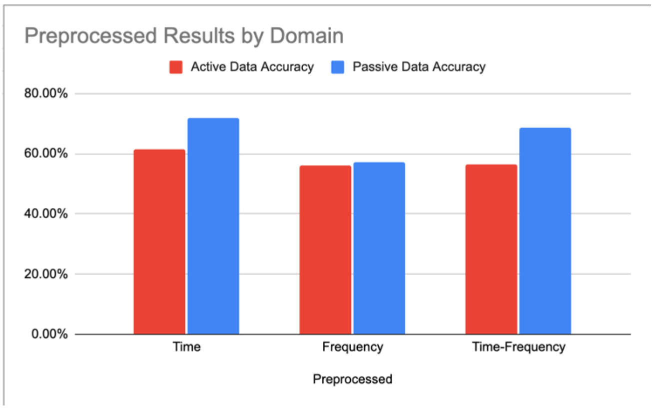

Fig. 23 – Preprocessed Data Domain Results.

The final averages generated from the experiments performed on preprocessed data included 63.67% Active Validation Accuracy and 81.78% Passive Validation Accuracy. For training data, the results were 18.73% more accurate when differentiating between passive data than it was with active data. Similarly, with the validation data, passive sleepy vs passive awake results were 18.11% accurate than active awake vs active sleepy. Although the accuracy for preprocessed data overall decreased, the model's differentiation percentage became more accurate with preprocessed data than it originally was with raw data. Overall, our results remained consist with our initial prediction.

C. *Overall Results*

The experiments conducted in our study covered a wide range of topics related to EEG and attention, in order to test what could be done with the data we collected. The experiment outlined in Index 1 was the main focus of our research: comparing active attention tasks to passive attention tasks. Table I explains the experiments along with their results in detail.

Table I Explanation of Research Experiments with Results		
Index	**Experiment**	**Result**
1	Active attention energy state differentiation versus passive attention energy state differentiation	Models were better able to differentiate passive task energy state than active task energy state.
2	Effect of the number of sensors on the accuracy of model prediction results	As the number of sensors decreased so did model accuracy. However, even with as few as three sensors, models maintained acceptable accuracy. See Fig. 16 and Fig 20.
3	Effect of the location of small groups of sensors on the accuracy of model prediction results	For unprocessed data, the sensors at the front of the head yielded the greatest accuracy. For preprocessed data, sensors at the back of the head yielded the greatest accuracy. See Fig. 17 and Fig. 21.
4	Effect of domain (time verses frequency) on the accuracy of model prediction results	Untransformed (raw) data yielded the greatest accuracy with both unprocessed and preprocessed data. See Fig. 19 and Fig. 23.
5	Effect of band size on the accuracy of models trained using Fourier transformed data	For unprocessed data, fewer bands yielded greater accuracy. For processed data, the number of bands had little effect on accuracy. See Fig. 18 and Fig. 22.
6	Effect of the type of preprocessing used on the accuracy of model results	Data processed using MNE-Python yielded greater accuracy then data processed using EEGLab.
7	Effect of the number of subjects on the accuracy of model prediction results	For unprocessed data, fewer subjects resulted in greater accuracy. For preprocessed data, the number of subjects had little effect on accuracy.
8	Effect of the source of data on model accuracy	Data from the DSI-24 yielded greater accuracy than the STEW data.

V. CONCLUSION

Whether a subject is alert or fatigued, the mental workload will still use the same amount of resources during tasks that require active attention. The mental workload seems to be exacerbated during passive tasks when a subject is tired. This data is understood by the accuracy of the 3DCNN when classifying the data. The 3DCNN has a more difficult time deciphering between active tasks that were performed when the subject was alert versus when they were sleepy, than the passive task counterpart. From this result, it can be understood that students who are watching lectures or performing other passive tasks will see a decrease in efficient learning when they are tired. However, students who are performing active tasks will use a similar amount of resources whether they are tired or wide awake. It is still recommended that students get plenty of rest each night, as there are major wellness benefits associated with obtaining more than 6 hours of sleep.

A GitHub repository has been created for the 3DCNN code and data used throughout this study. Please visit the following link to view: https://github.com/mkwarman/Active-Passive-Attention-3DCNN-Classification.

APPENDIX

Comparison of Active and Passive Attention Based Tasks Using EEG Waves with Convolutional Neural Network

Data Collection Plan

Our data collection process will consist of six trials, each with a duration of thirty seconds. These trials are broken up into two categories: Attention and Mental Workload to test various everyday functions that will trigger brain activity. We will conduct each trial twice, once in a state of being wide awake and another in the state of being sleepy. The brain activity will be recorded by the Wearable Sensing EEG headset. The trials will be conducted by Alyssa Myers, Jasmine Hemphill, and Sowmya Javvadi.

Attention Trials

Trial 1 – Eye Tracking

- Concentration Based
- Duration: 30 seconds
- The test subject will look at a white screen and follow the movements of a computer mouse.

Trial 2 – Listening to Music

- Concentration Based
- Duration: 30 seconds
- The test subject will listen to a song with their eyes closed.

Trial 3 – Watching a Video

- Concentration Based
- Duration: 30 seconds
- The test subject will watch a video explaining how to write a program (coding)

Mental Workload Trials

Trial 4 – 2048 Game

- Concentration Based
- Duration: 30 seconds
- The test subject will play a math game.

(https://www.coolmathgames.com/0-2048)

Trial 5 – I Spy Game

- Concentration Based
- Duration: 30 seconds
- The test subject will play a game where they have to find items on a list.

(https://www.sporcle.com/games/Stanford0008/i-spy-4-clickable)

Trial 6 – Memory Cards

- Concentration Based
- Duration: 30 seconds
- The test subject will watch a pattern flash across the screen, and they have to try and repeat that pattern.

(https://www.assessmentday.com/free/gamified/memory-cards/memory-cards.html)

Fig. 24 – Data Collection Plan.

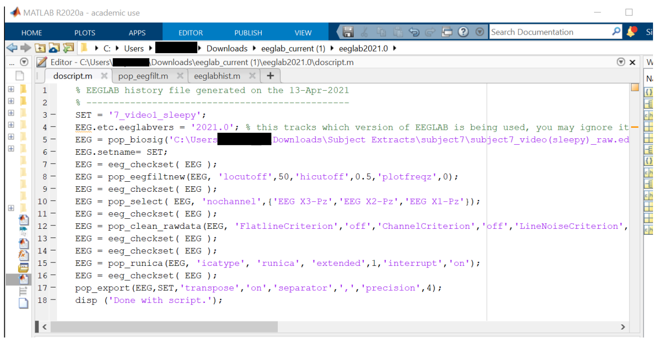

Fig. 25 – EEGLab Preprocessing Script.

```python
def preprocess_file(filename, input_directory, output_directory):
    data = np.loadtxt(input_directory + '/' + filename, delimiter=',',
                      skiprows=1, usecols=[*range(0, 25)])
    times = data[:, 0]

    transposed_sensors = np.transpose(data[:, 1:])

    # Rescale baseline
    rescaled = mne.baseline.rescale(transposed_sensors, times, (0, .1))

    info = mne.create_info(COLUMNS, HERTZ, ch_types='eeg')
    raw = mne.io.RawArray(rescaled, info)

    # Remove unused sensors
    raw.drop_channels(['X1', 'X2', 'X3'])

    # Lowpass 50Hz, Highpass 0.5Hz
    raw.filter(0.5, 50., fir_design='firwin')

    # Rereference to common mode follower
    raw.set_eeg_reference(ref_channels=['CM'])

    # Remove common channel after using it as a reference
    raw.drop_channels(['CM'])

    name = output_directory + '/' + 'preprocessed_' + filename
    header = str(raw.ch_names).strip("[]").replace("'", "")

    np.savetxt(name, np.transpose(raw.get_data()), delimiter=",",
               header=header, comments="")
```
Fig. 26 – MNE-Python Preprocessing Script.

Acknowledgment

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