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Introduction and Background

Our Data Set: https://huggingface.co/datasets/DavidVivancos/MindBigData2022

Interpreting brain signals as responses to visual stimuli is an exciting topic of research, with a wide variety of applications in healthcare [1], education [2], and entertainment [3]. These signals can be easily obtained using electroencephalograms (EEG), which employ signal processing techniques like Fourier transforms and spectral analysis to generate meaningful interpretations [4]. Numerical digits are commonly chosen as stimuli in this research because they are discrete, limited in number (0-9), and universally understood [5, 6].

Our data set was developed by David Vivancos, who used 4 different EEG machines to track activity in 19 sections of his own brain upon being shown an image of a single digit at a time. These images ranged from 0-9, or no digit as a control. EEG machines obtain data by placing electrodes, known as “channels,” on different brain regions and recording voltage fluctuations as a time series over a 2-second time interval. Depending on the machine, between 256 and 1024 data samples will be taken simultaneously at each channel during this time period.

The dataset includes 4 main sub-datasets for each EEG machine used. For each subset, there exists a “digit” feature corresponding to the digit shown, an “event id” to catalog unique number-showing events, a “brain region” to map the location from where an electrode made its reading. Finally, there are 256-1024 columns of time series data sampled that correspond to the amplitudes of electric intensities measured from the given “brain region”.

For each “event,” there will be one row of time-series data corresponding to each electrode channel. Therefore, for our purposes, a datapoint can be considered all rows which share the same “event id” – 19 for the full data set.

For this report, we have elected to focus on two EEG machines for a preliminary understanding of the problem space – the Emotiv Insight machine and MUSE machine. These machines collect 256 data samples at each electrode channel over the 2-second time interval, corresponding to a frequency of 128 Hz. This data collection happens simultaneously at 5 electrode channels for the

Inisght machine (4 for MUSE), so each “event id” will correspond to 5 rows of time-series data. Future development will extend the model from the Insight and MUSE machines to the other EEG machines.

Problem Definition

We seek to develop an accurate system of decoding brain signals associated with specific visual stimuli, in this case related to numerical digits. Each digit is expected to generate unique amplitudes and intensity patterns in each electrode channel, so a machine learning model can be developed to predict the digit seen based on this time-series data. Through our model, it will be possible to predict what digit is being seen by the candidate given their brain activity.

This research will be applicable in proving the feasibility of brain-computer interfaces (BCI’s), which have immense potential for improving quality of life for individuals experiencing disabilities in physical or verbal communication. Brain-computer interfaces operate by translating electrical signals from the brain into commands that can be applied to a computer or other device [3]. As a result, when methods such as typing, speaking, or gesture-based systems are inaccessible, BCIs that solely rely on brain activity could minimize this accessibility gap.

Methods

Previously, we preprocessed the data by reducing each time series to its core summary statistics, max, min, mean, and range since data points can be characterized as all rows that share an “event id”. We then trained Logistic Regression, Random Forest, and Gradient Boosting supervised learning models on the preprocessed data.

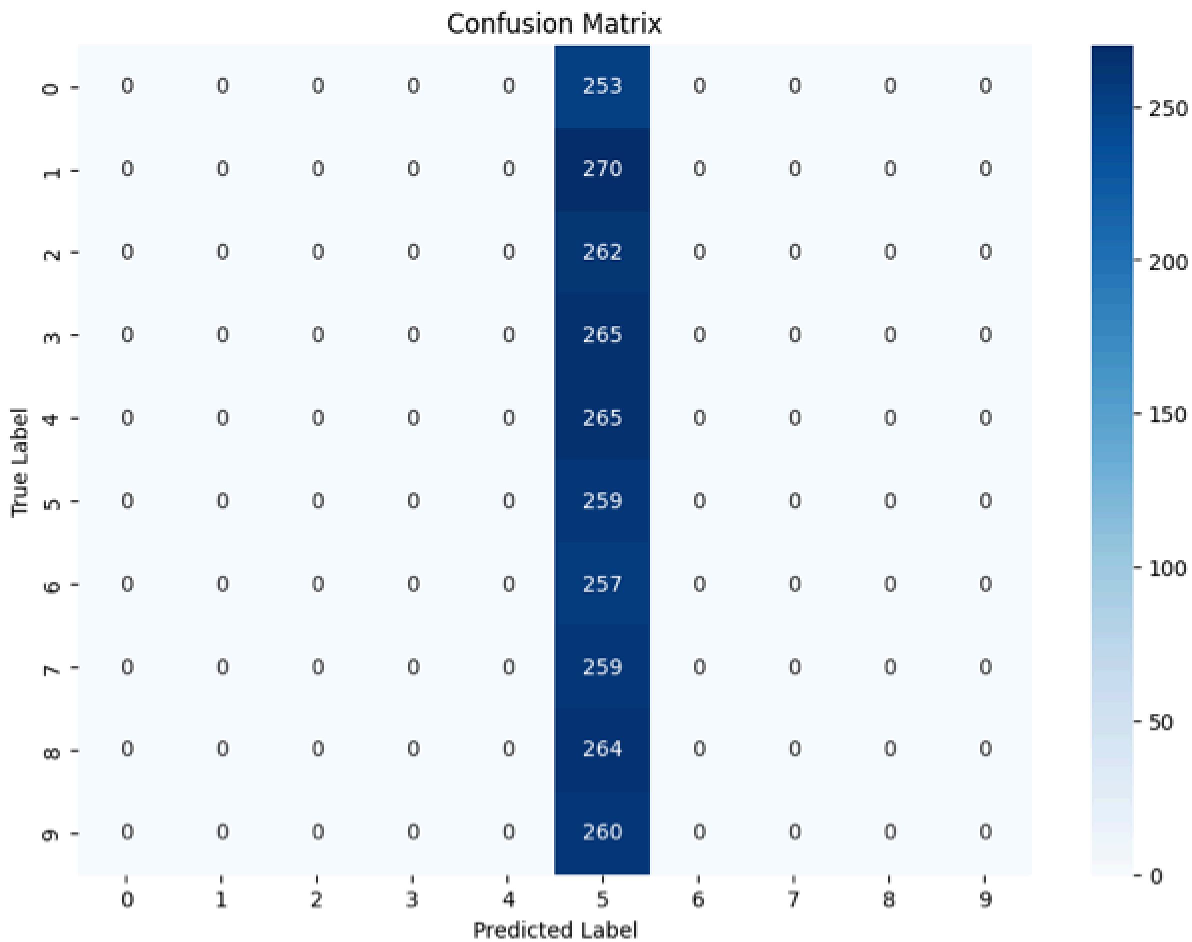
However we took a vastly different approach this time as all models with varying amounts of hyperparameter tuning were essentially guessing. We switched Logistic Regression with a Convolutional Neural Network where we used the raw data since it handles time-series well. For the CNN, we took the raw data, standardized it for the neural network, and imputed the missing values with column means.

However for the Random Forest and Gradient Boosting models, we kept the critical statistics but also added in the expanded data set which has approximately 2 times as many data points across 4 different brain regions. This was also standardized, and for Random Forest, performance was boosted after using a PCA to reduce the number of components.

Results and Discussion

Recurrent Neural Network (RNN):

Accuracy Score: 11.13%, F1 Score: 9.91%



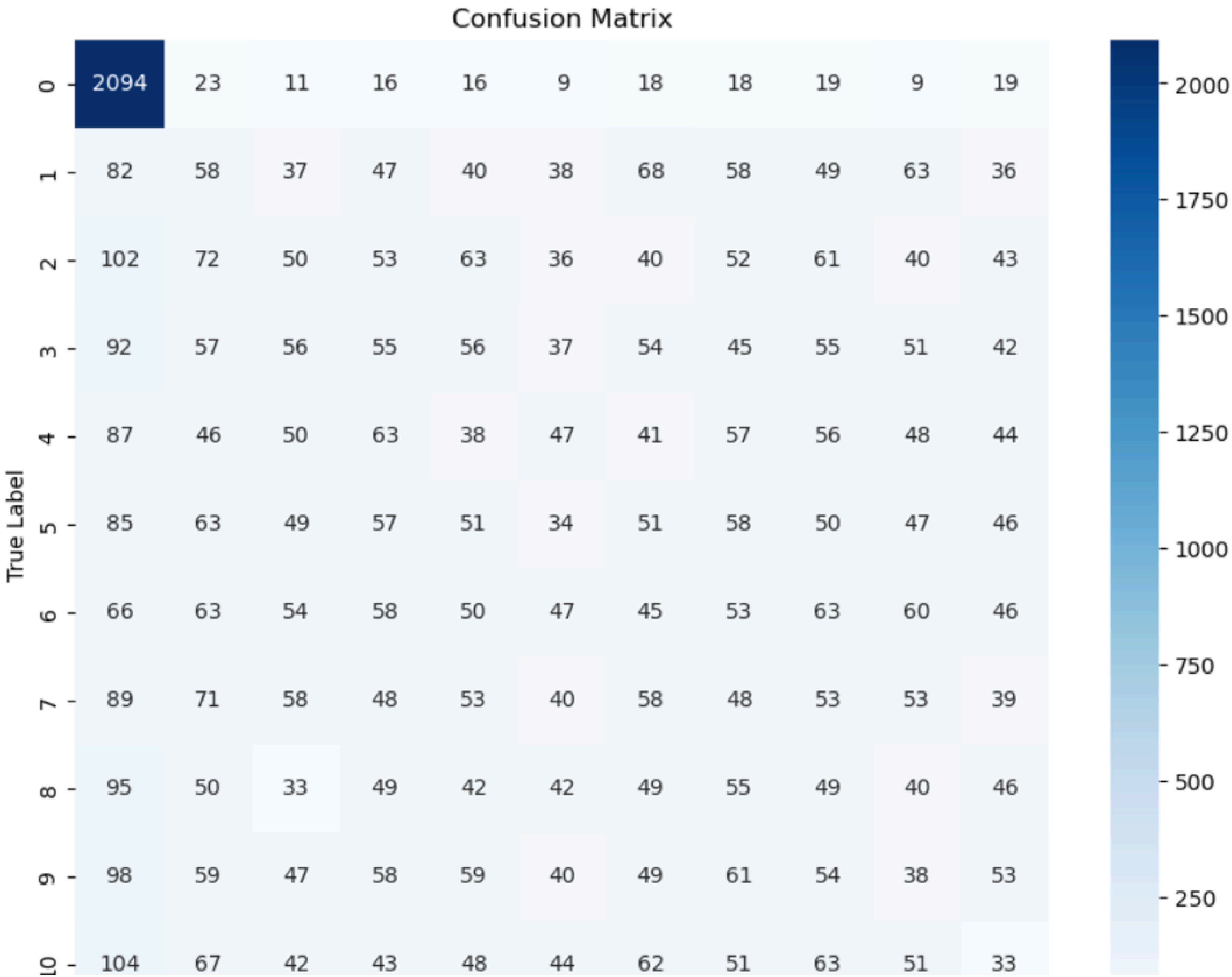
Gradient Boosting:

Accuracy Score: 31.50%, F1 Score: 27.45%

```
Top 10 Most Important Features:
      feature  importance
3     TP9_Max    0.401533
0     FP1_Max    0.211166
12    FP1_Min    0.072736
15    TP9_Min    0.051715
16    FP1_Std    0.046082
17    FP2_Std    0.033647
18   TP10_Std    0.022964
13    FP2_Min    0.019309
4    FP1_Mean    0.019278
19    TP9_Std    0.018890
```

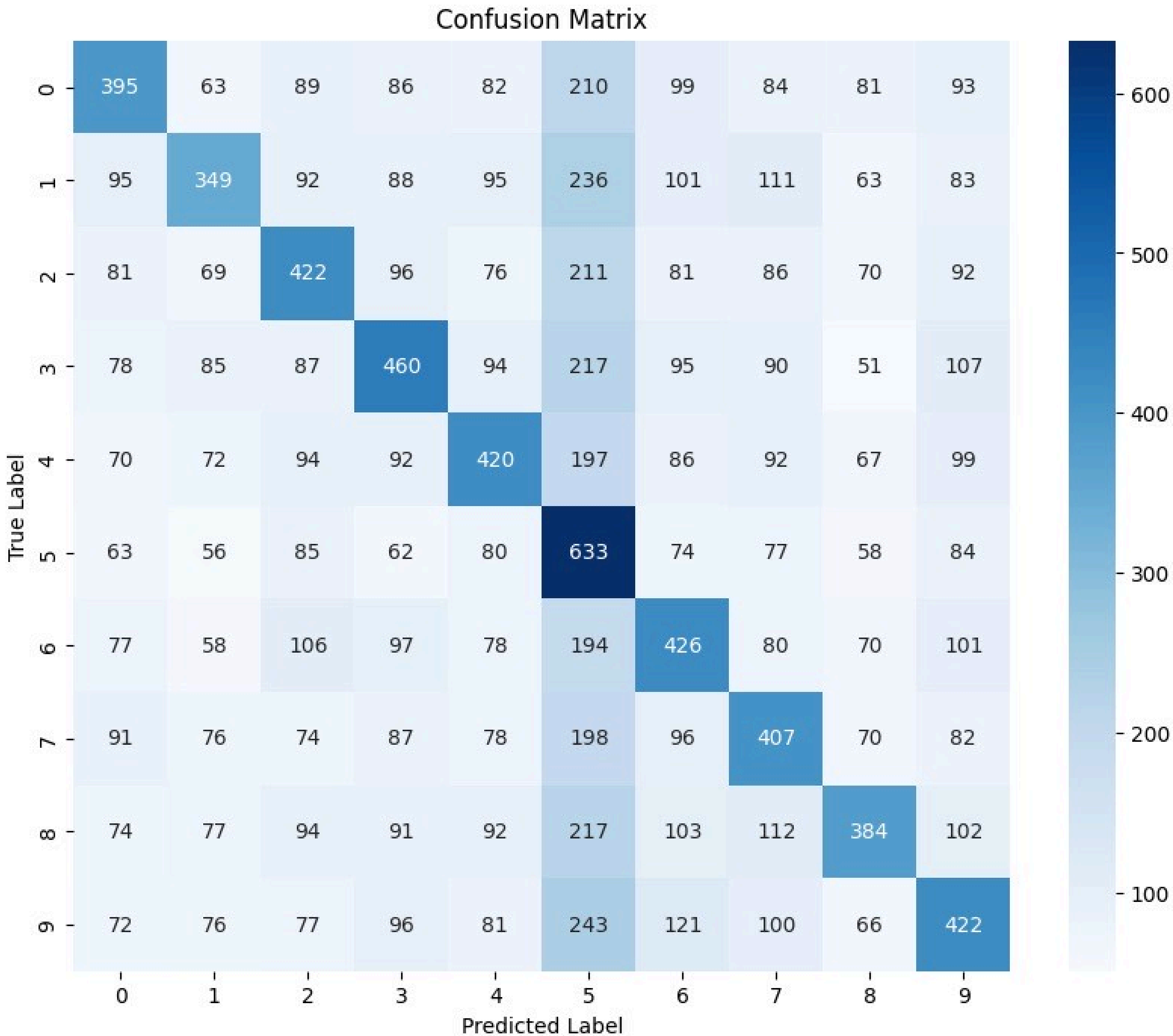
Random Forest:

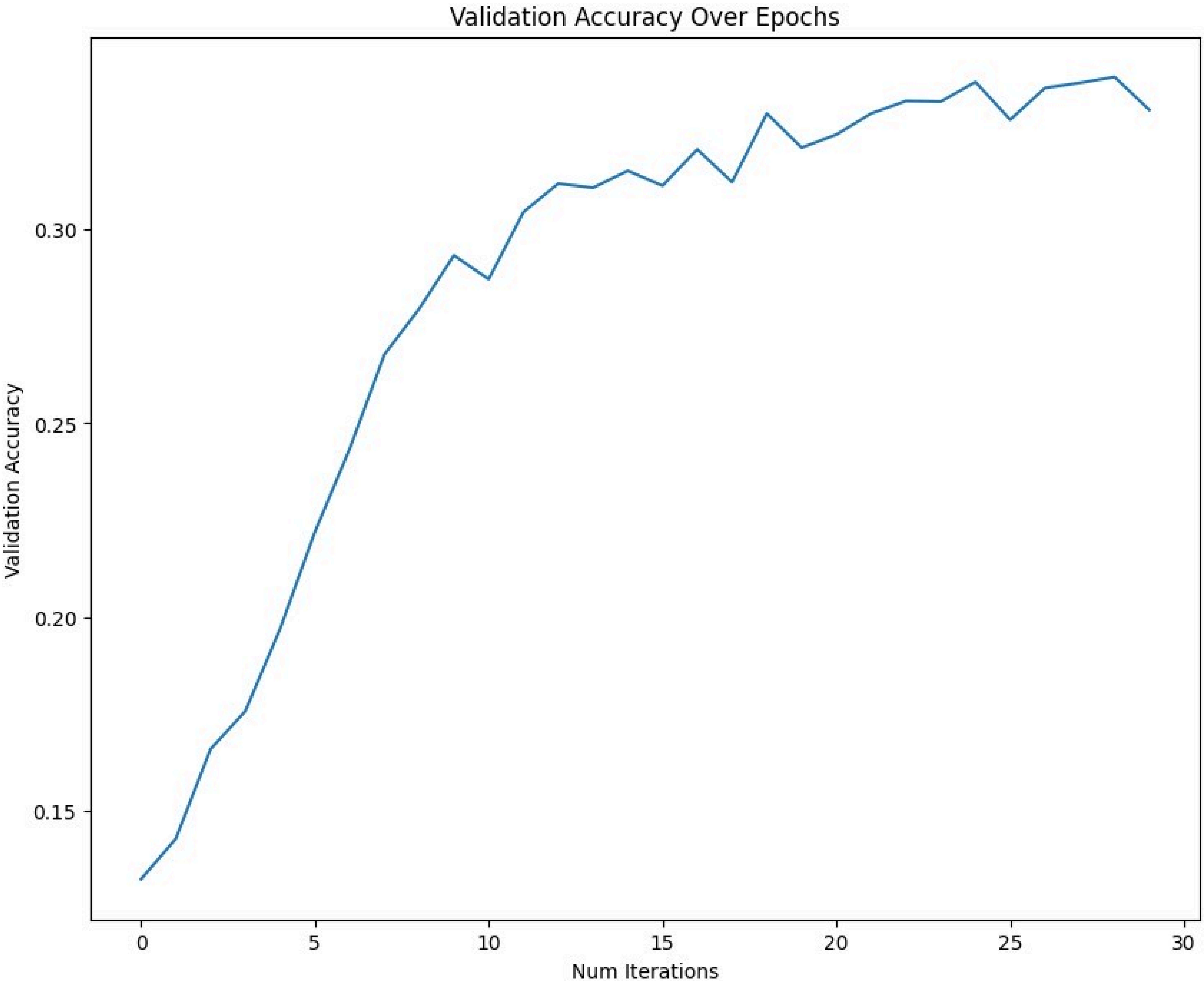
Accuracy: 31.01%, F1 Score: 27.73%


Confusion Matrix
True Label
0 2094 23 11 16 16 9 18 18 19 9 19
1 82 58 37 47 40 38 68 58 49 63 36
2 102 72 50 53 63 36 40 52 61 40 43
3 92 57 56 55 56 37 54 45 55 51 42
4 87 46 50 63 38 47 41 57 56 48 44
5 85 63 49 57 51 34 51 58 50 47 46
6 66 63 54 58 50 47 45 53 63 60 46
7 89 71 58 48 53 40 58 48 53 53 39
8 95 50 33 49 42 42 49 55 49 40 46
9 98 59 47 58 59 40 49 61 54 38 53
10 104 67 42 43 48 44 62 51 63 51 33
2000
1750
1500
1250
1000
750
500
250

Convolutional Neural Network (CNN):

Accuracy Score: 34.00%, F1 Score: 33.06%


Confusion Matrix
True Label
Predicted Label
0
1
2
3
4
5
6
7
8
9
395 63 89 86 82 210 99 84 81 93
95 349 92 88 95 236 101 111 63 83
81 69 422 96 76 211 81 86 70 92
78 85 87 460 94 217 95 90 51 107
70 72 94 92 420 197 86 92 67 99
63 56 85 62 80 633 74 77 58 84
77 58 106 97 78 194 426 80 70 101
91 76 74 87 78 198 96 407 70 82
74 77 94 91 92 217 103 112 384 102
72 76 77 96 81 243 121 100 66 422
600
500
400
300
200
100


Validation Accuracy Over Epochs
Validation Accuracy
0.15
0.20
0.25
0.30
0
5
10
15
20
25
30
Num Iterations

Analysis and Comparison of Models

Our new iteration compared Recurrent Neural Network, Gradient Boosting, Random Forest, and CNN models to decode EEG signals. The Recurrent Neural Network performed the worst, essentially guessing the same random number 100% of the time. This was not expected, as the strength of an RNN is to handle time series data. However, there are many facets that could be tapped into, such as tuning the hyperparameters and training the model with more layers. Gradient Boosting provided valuable insights into feature importance but lacked specificity for handling time-series EEG data. Random Forest, while efficient, produced poor true accuracy and F1 scores, making it unsuitable for our application despite enhancements like PCA. This is because we failed to consider the heavy class imbalance associated with the expanded data set and, thus, our model “learned” only to predict based on the imbalance. The CNN’s success underscores its suitability for time-series EEG data, particularly in identifying patterns across multiple electrode channels. However, the increased complexity required significant processing power, which limited our ability to test on larger datasets. While Gradient Boosting and Random Forest offered value in terms of interpretability and efficiency, their limitations in modeling temporal dependencies emphasize the need for tailored approaches like CNNs when dealing with sequential data. These findings validate the potential of neural networks for EEG-based classification tasks, paving the way for further exploration in brain-computer interface development.

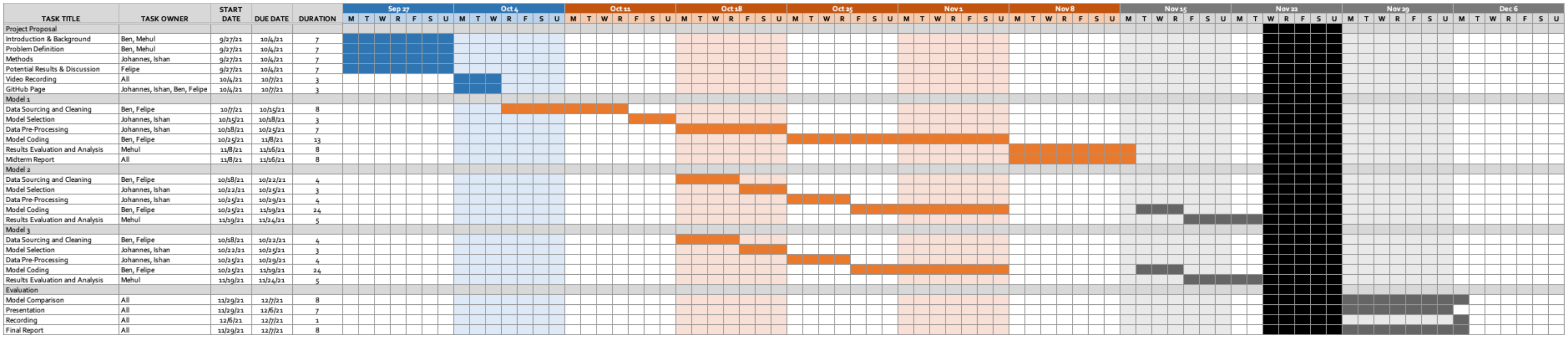
Next Steps

Our models, while much improved, were still limited by the processing power we had available. For example, we were unable to test them on larger datasets because of the amount of time and energy it would consume on our personal computers. For example, the CNN and RNN took about 1 minute per epoch on the smallest data set and would take about 5 minutes on the larger data sets. Additionally, we suspect that training on the larger data set would assauge the overfitting that occurs for the CNN. For the future, resources like Google Colab would allow us to obtain access to more powerful GPUs for further exploration of this problem space.

Additionally, the Random Forest model was limited by the overly simplified representation of EEG signals and failure to consider class imbalance. Reducing each time series to basic summary statistics (max, min, mean, range) likely discarded essential temporal information, which is crucial in brainwave analysis.

In the future, we plan to make several enhancements. First, we will incorporate Fourier Transforms to shift EEG data into the frequency domain, allowing us to capture patterns in specific frequency bands associated with cognitive states. By applying PCA on these Fourier-transformed features, we hope to retain important patterns while reducing dimensionality. Additionally, we plan to explore Long Short-Term Memory networks (LSTMs) as they are better-equipped for time-series data and can capture sequential dependencies, whereas logistic regression and random forest are used for independent data points.

Gantt Chart:



Contribution Chart:

Name	Proposal Contributions	Midterm Contributions	Final Contributions
Ishan Sheth	Methods, Gantt Chart, Contribution Table, Video Recording	Model 1 Coding , Model Research, Results and Discussion, Video Recording	Model 1 and 2 Coding , Model Research, Results and Discussion, Video Recording
Johannes Qian	Methods, GitHub Page, Video Recording	Model 1 Coding, Model Research, Results and Discussion, GitHub Page, Video Recording	Model Research, Results and Discussion, RNN Development, GitHub Page, Video Recording
Felipe Bergerman	Potential Results & Discussion, Video Recording	Data Pre-Processing, Model Research, Next Steps, Video Recording	Model Research, CNN Model development, Next Steps, Video Recording
Mehul Dhoot	Introduction & Background, Problem Definition, Video Recording	Data Cleaning, Model Research, Video Recording	Feature Engineering, Model Research, Model Comparison, Next Steps, Video Recording
Benjamin Madar	Introduction & Dataset, Problem Definition, Gantt Chart, Contribution Table, Video Recording	Data Extraction, Data Cleaning, Model Research, Gantt Chart, Contribution Table, Video Recording	Model Research, Feature Engineering, Models 1 and 2 development, Gantt Chart, Contribution Table, Video Recording

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