UCLA Undergraduate
RESEARCH WEEK

A Machine Learning Model for Classifying Drowsiness from Electroencephalogram Data

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Key Points

- Electroencephalogram (EEG) data is useful for objectively determining levels of drowsiness.
- Single-channel EEG data was used to develop binary machine learning classification models.
- Support Vector Machine (SVM) was determined to be the optimal model for commercial use.
- Model will be tested on live EEG data.

Introduction

- **Drowsiness:** An abnormal feeling of sleepiness during the day. Associated with a decrease in cortical processing efficiency. Causes issues in instances including driving, learning, and hunger.
- **Project Goal:** Use machine learning methods to develop a drowsiness classifier based on existing EEG data and implement this model to conduct real-time drowsiness classification on individuals. Reduce human tragedy in monitoring and informing people of their drowsiness levels, allowing them to perform better or opt out of tasks otherwise inhibited by drowsiness.

Methods

Extract data from Physionet Sleep EDF Database

Convert raw data to epochs and annotations, preprocess data

Perform Feature Extraction and Selection

Input data into classification models: Support Vector Machine, Random Forest, Convolutional Neural Network

Test Model on live EEG Signals

Figure 1. Flowchart of model creation and testing

Results

Comparing 3 different classifiers, SVM had the highest accuracy over 24 epochs, while Random Forest had the highest accuracy with 50 epochs

Classifier	Accuracy over 24 epochs	Accuracy over 50 epochs
SVM	0.750	0.772
Random Forest	0.707	0.804
CNN	0.533	0.533

Figure 2. Evaluation of classifier performance on test set

Results

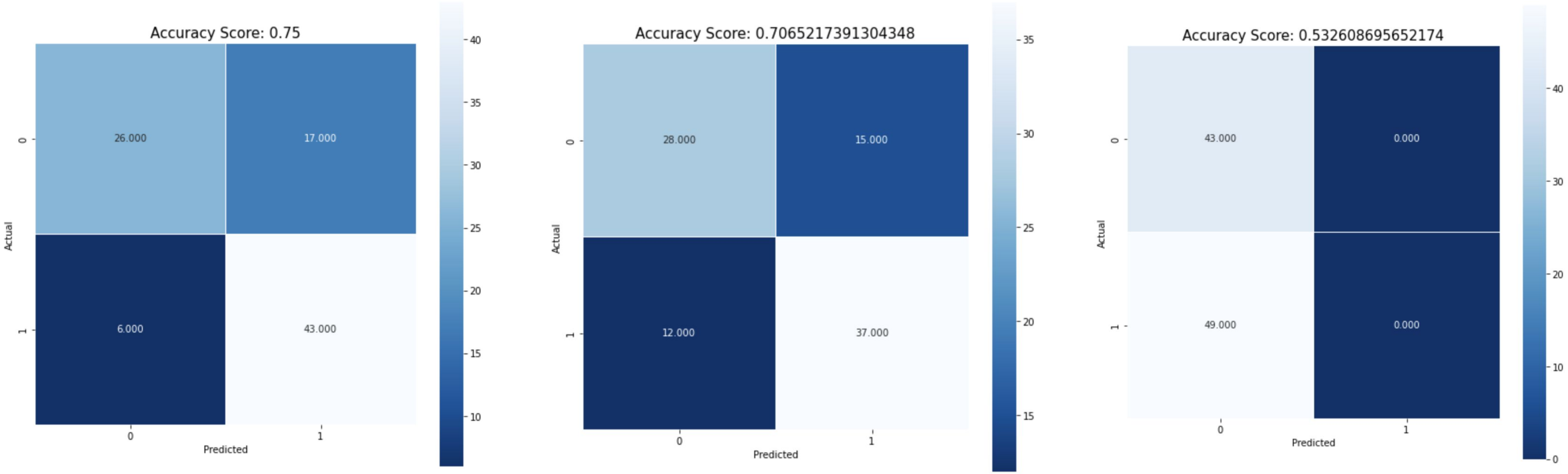

Figure 3. Confusion matrices for SVM, Random Forest, and CNN classifiers trained and tested on 24 five-second epochs

Discussion

- **24** epochs: **SVM** > Random Forest >> CNN
  50 epochs: **Random Forest** > SVM >> CNN
  - SVM and Random Forest approached the maximum accuracy rates of automatic sleep stage classifiers, but CNN performed poorly, failing to detect drowsiness.
  - Increasing the number of epochs tended to improve model accuracy.
- **SVM** maximizes accuracy and real-world applicability.

Discussion

Limitations

1. Subjects in data set were ages 25 and above.
2. Models were trained on single-channel EEG data.
3. CNN was trained on a limited number of hand-crafted features.
4. Models were trained on EEG data collected solely during wake and light sleep.
5. Models were tested on a limited number of epochs collected at a non-random time point during sleep stages.

Conclusion and Future Experimentation

- Future experimentation:
  - Test different models and/or features in order to increase accuracy
  - Validate model with more age-diverse datasets
  - Refine model to include multi-class classifications
- App development
- Test on live EEG data using MUSE headset

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