Abstract—This paper presents a model for predicting a driver’s stress level up to one minute in advance. Successfully predicting future stress would allow stress mitigation to begin before the subject becomes stressed, reducing or possibly avoiding the performance penalties of stress. The proposed model takes features extracted from Galvanic Skin Response (GSR) signals on the foot and hand and Respiration and Electrocardiogram (ECG) signals from the chest of the driver. The data used to train the model was retrieved from an existing database and then processed to create statistical and frequency features. A total of 42 features were extracted from the data and then expanded into a total of 252 features by grouping the data and taking six statistical measurements of each group for each feature. A Random Forest Classifier was trained and evaluated using a leave-one-subject-out testing approach. The model achieved 94% average accuracy on the test data. Results indicate that the model performs well and could be used as part of a vehicle stress prevention system.

Index Terms—Galvanic Skin Response (GSR), Electrocardiogram (ECG), Respiration, Stress, Machine Learning, Future Stress Prediction

I. INTRODUCTION

High levels of stress impair task performance and can lead to accidents while driving [1]. Stress detection can aid the mitigation of stress only after the subject has become stressed. A method of predicting stress in advance could improve stress mitigation strategies by allowing stress mitigation to begin before the subject enters a stressed state.

Detection of physiological stress has been addressed in numerous papers, either by simple correlation with physiological data [2] or by the use of machine learning algorithms [3] [4]. We have been unable to find any paper which has attempted to use machine learning to predict the stress level of a subject sometime before the subject enters the “stressed” state. Early prediction of stress has the advantage of allowing stress mitigation methods to begin before the subject is stressed, ideally negating the decreased task performance associated with stress.

In this work, we propose a model which predicts approaching stress, rather than the current stress level of the subject. If used in conjunction with a car entertainment system or smartphone, this model could be used to launch an intervention to decrease the subject’s stress before it rises above a certain threshold. An overview of such a system is presented in Figure 1.

II. PROPOSED WORK

Figure 2 shows a diagram representing the proposed stress prediction model. The model begins with data preprocessing, feature extraction, and feature expansion. The extracted features are then separated into training and test data following a leave-one-subject-out (LOSO) testing approach. The training data is used to train a random forest classifier, the performance of which is then measured using the test data. We propose the following hypothesis to explore the possibility of predicting stress using this model.
**Hypothesis 1.** If \( x(t) \) denotes the physiological feature space at time \( t \) and \( y(t) \) denotes the subject’s stress level at time \( t \), then it is possible to develop a stress model \( M \) trained on \( x(t-1:t-n) \), where \( n \) is the number of time steps used to train the model, that can predict \( y(t) \) with good accuracy.

We will present the data used to train the stress prediction model, the model itself, and discuss the performance of the model on test data. Four different values of \( n \), \( n = 2, 3, 4, \) and 5, will be tested in the feature expansion phase of the model and evaluated. We will be training the model with data consisting of six of our seven subjects and we will test the accuracy of the trained model using the remaining subject, following the LOSO testing approach. The experimental data used in this work is a subset of the data collected in [7].

### III. Data Analysis

The data analysis of the stress prediction model is divided into three phases: (i) Data Preprocessing, (ii) Feature Extraction, (iii) Feature Expansion. Feature selection was considered but did not show any performance improvement. The overview of the system is shown in Figure 2.

#### A. Data Preprocessing

The data preprocessing module consists of three stages. The first stage normalizes the GSR, Respiration, and ECG signals to be within the range of 0 to 1. The second stage uses a Butterworth filter of 5 order to filter off signal components that are higher than 1 Hz for the GSR signals, 10 Hz for the respiration signal, and 40 Hz for the ECG signal. The third stage integrates the signals from different time periods of the experiment for feature extraction.

#### B. Feature Extraction

The feature extraction module consists of three parts, one for each type of physiological signal. All of the features extracted from the physiological signals were calculated over a running 100 second window with a 50 second overlap.

1) **GSR Feature Extraction:** A total of 7 features were extracted from both the hand and foot GSR signals. Two features, the mean and variance, were taken from the original signal, while the remainder are based on the peaks in the signal. The peaks are detected by applying a peak
finding algorithm [9] to the first derivative of the GSR signal. The features derived from the peaks are the number of peaks occurring in a window, the sum of the peak amplitudes and duration, and the mean and variance of the peak prominence.

2) Respiration Feature Extraction: A total of 6 features were extracted from the respiration signal. There are two statistical features: the mean and variance of the signal, and four frequency features: the power in the 0-0.1 Hz, 0.1-0.2 Hz, 0.2-0.3 Hz, and 0.3-0.4 Hz bands. These were extracted by computing a periodogram for the signal and using and algorithm [10] to calculate the band power on the desired bands.

3) ECG Feature Extraction: A total of 22 features were extracted from the ECG signal based on Heart Rate (HR) and Heart Rate Variability (HRV). These features were calculated by applying algorithms in [11] to extract time and frequency domain features from the ECG signal. The time-domain features include statistical features relating to HRV and the mean, maximum, minimum, and standard deviation of the heart rate. The frequency-domain features include the total power in the signal, the power in the very low frequency (VLF, 0.003 to 0.04 Hz), low frequency (LF, 0.04 to 0.15 Hz), and high frequency (HF, 0.15 to 0.40 Hz) bands, the ratio of the LF to HF bands, and the normalized LF and HF power.

C. Feature Expansion

In the feature expansion unit, all of the 42 total features extracted from the GSR, Respiration, and ECG signals were expanded into 6 new features. These new features consist of the mean, median, standard deviation, minimum, maximum, and time-weighted average of the original features in groups of n data points each. In order to focus on predicting transitions between stress levels, only the last n data points for each driving section were expanded and passed to the next stage. To find an optimal value for n, four expanded feature sets are generated by performing feature expansion with n = 2, 3, 4, and 5.

Each data point is also labeled low, medium, or high stress depending on the driving situation (Rest, Highway, or City, respectively), and the label and 252 features are packed into a data frame. At this point, the labels for each driving section were expanded and passed to the next stage. To find an optimal value for n, four expanded feature sets are generated by performing feature expansion with n = 2, 3, 4, and 5.

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IV. Results

In this section, we will discuss the performance of the fitted models on the test data. The model is trained by fitting a random forest classifier with 100 estimators using the Gini function and a maximum depth of 30 to the training set. The train and test sets are selected using the leave-one-subject-out testing approach, meaning that a drive is selected for the test set with the remaining drives composing the train set. After the model is evaluated, a different drive is selected for the test set such that each drive is selected once. This approach is repeated with each of the four expanded feature sets. The model is evaluated based on accuracy classifying the training and test data, and F1-score on the test data. The precision, recall, and F1-score of the model on the test data are also measured for the high and low-stress categories.

From Figure 3 it may be seen that the model has good performance for all tested values of n. Additionally, there appears to be a positive, linear relationship between n and model performance. The clear exception to this relationship is the F1-score of the low-stress category for n = 2, which is better than n = 3 or 4. Table I displays the low stress F1-score in more detail. It is clear that the low average performance is due to poor performance in classifying the low-stress situation in drive 10. This discrepancy appears to be the result of an unusual physiological reaction by the driver.

The best results were generated from the n = 5 case. Table I shows the average precision and recall of the model. The precision and recall for the low-stress scenario are 0.95 and 0.93, respectively, which indicates that the model both predicts the low-stress state effectively and has a low rate of incorrectly classifying low-stress as high-stress. The precision and recall for the high stress scenario are 0.96 and 0.95, respectively, which indicates that the model both predicts the high stress state effectively and has a low rate of incorrectly classifying high stress as low stress. The performance data indicates that our hypothesis has promise. A stress model M trained on $x(t - 1 : t - n)$ has predicted $y(t)$ with good accuracy, as stated in our hypothesis.
TABLE I: Low Stress F1-Score as \( n \) Changes

| \( n \backslash \text{Drive No.} \) | 5   | 6   | 7   | 10  | 11  | 12  | 15  |
|-----------------|-----|-----|-----|-----|-----|-----|-----|
| 2               | 0.80| 1.00| 1.00| 0.67| 0.67| 1.00| 0.67|
| 3               | 0.80| 1.00| 1.00| 0.00| 1.00| 0.80| 0.67|
| 4               | 0.80| 1.00| 1.00| 0.00| 1.00| 0.80| 1.00|
| 5               | 0.80| 1.00| 1.00| 0.67| 1.00| 1.00| 1.00|

TABLE II: Precision and Recall of the Predictive Model

|          | Precision | Recall | F1-Score |
|--------|-----------|--------|---------|
| Low Stress | 0.95      | 0.93   | 0.92    |
| High Stress| 0.96      | 0.95   | 0.95    |
| Weighted Average | 0.96    | 0.94   | 0.94    |

V. DISCUSSIONS

The physiological data used in this study is composed only of data from subjects as they completed a specific driving route through Boston. While the consistency of the data has the desirable property of revealing differences between individuals, it also makes it very difficult to create a generalized model. As a result, the current model may perform more poorly on data collected from a different driving route. Additionally, the ground truth used to train this model assumes that the road type is an accurate sole indicator of subjective stress. While this is a reasonable starting point, subjective stress could also be influenced by other drivers, weather conditions, or other occurrences which can vary independently of the road type.

VI. FUTURE RESEARCH DIRECTION

Data from different driving routes would improve the stress prediction model by refining the assumptions that it makes about how subjective stress is influenced by driving conditions. Another method of improving the model would be using a better subjective stress indicator as the ground truth, which could allow the model to account for more than just the effect that the road type has on the driver. This indicator would likely need to have an improved sample rate to more closely match the rate at which subjective stress can change. Cortisol has been explored as an indicator of stress \([12, 13]\), making it a potential candidate. With the aid of a newer type of sensor \([14]\), it can also be measured noninvasively in only a few seconds, making it an even more attractive candidate. Replacing the Random Forest Classifier with a deep neural network could also improve the model by removing the need for feature extraction and expansion. This would reduce the computational complexity of the model, thereby reducing the requirements for the edge device it operates on. A recurrent deep neural network has the added advantage of having the inherent ability to account for time dependency in input data, making it a good choice for this task.

VII. CONCLUSION

In this work, we have presented a stress prediction model which can predict the stress level of a subject up to one minute in advance. The model uses GSR, Respiratory, and ECG data taken while the subject is driving. The model then predicts whether the stress level of the subject will be high using \( n \) time steps of data prior to the period of interest. Performance data indicates an approximately linear increase in performance with increasing \( n \). The best performance of the model was at \( n = 5 \), where the model has an average test accuracy of 94%. This indicates that the model has good performance and could be expanded to include other driving situations.

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