Analyzing the Features and Efficacy of Classification Models for Physiological Stress Prediction

Motivation and Background

Motivation: Accurate stress prediction in law enforcement can serve to better prepare officers for the intensity of their work.

- **27%** of police officers suffer from symptoms of PTSD **[1]**
- **Concepts** in current stress prediction research:
- Healey [2] and the WESAD dataset [3] use physiological data.
- Standard supervised learning models (ex. RF, SVM) are used regularly [4].
- Deep learning in stress prediction has been attempted [5].

Goal:

- Compare conventional models with deep learning and investigates the effect of certain features and time ranges
- Generate results on the ideal algorithms and conditions for stress prediction.

Methodology

Data Collection



Participants

Training cadets at

the Phoenix Police

Regional Academy





Data collection + transfer



Processing

Feature Extraction

- Removal of non-responses and other noisy data
- Mapped biometric data to inputted stress levels based on certain time interval of relevance

Extracted Features	Heart Rate	Calories, METs, and Steps
	Mean, Max, Min, Std Dev, Regression Line, RMSSD, Resting Rate	Mean, Max, Min, Std Dev

Data Processing

- Binary classification threshold tuning down to 0.3 due to unbalanced dataset
- **SMOTE-ENN** for both over-sampling and under-sampling
- **Principal component analysis (PCA)** to reduce components
- Divided dataset into different intervals of time to investigate ROC_AUC • Intervals from **1 minute** to **3 hours**



Neural Network Development

Results





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Implemented two forms of neural network: CNN and MLP

 Convolutional Neural Network (CNN) • Reshaped dataset to fit Keras 1-Dimensional CNN • Implemented network with **convolutions**, pooling, flattening, and dropout.

• Multilayer Perceptron (MLP ANN) • Created **MLP Classifier** with **4 hidden layers**



Efficacy of Each Model Type

ROC_AUC Score vs Time Frame

ROC_AUC Score Analysis Across Different Time Intervals



Comparison of 5 Strongest Models

Model Type	Accuracy %	Recall %	ROC_AUC %
Random Forest	0.694	0.802	0.738
XG Boost	0.755	0.697	0.737
Decision Tree	0.762	0.613	0.696
MLP ANN	0.775	0.67	0.737
CNN	0.784	0.674	0.738

Feature Importance for 5 Strongest Models

Feature	
Resting Heart Rate	Rar
RMSSD (Root Mean Squared of Successive Differences)	Rar
Max Steps	Rand
Mean HR	Rand

Model

ndom Forest, XG Boost, **Decision Tree**

ndom Forest, XG Boost

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Conclusions

- **RF, XG Boost, and Decision Tree** are best at stress prediction among common models
- Consistent with previous studies [4]
- Neural network models performed equally well or **better** for overall metrics
 - Good potential for further use of deep learning in stress prediction
- Larger time windows (up to 3 hours) yielded better accuracies
- More data outweighs more relevant timeframe
- Strong correlation between **heart related metrics** and model efficacy

Future Work

- Test latency of real-time stress prediction on Fitbit mobile devices
- Compare efficiencies of larger **deep learning** models on mobile devices with efficiencies of standard supervised learning models
- Consider addition of **other features** such as location contextualization or emotional responses

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References and Related Works

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