EMOTION RECOGNITION USING EEG SIGNALS AND WRIST BAND DATA

PROJECT GROUP (SS24)

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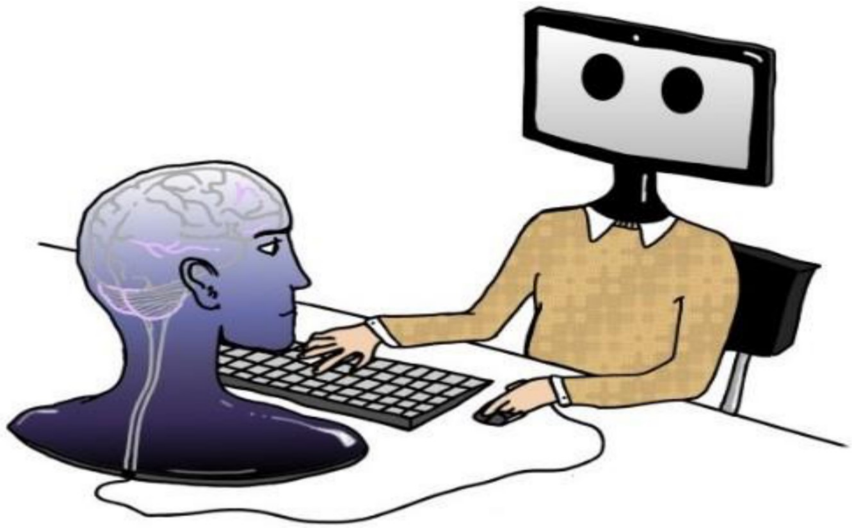
Motivation

Why does emotion detection matter?

- Imagine devices that understand how you feel, that can actually respond to your emotions in real-time.



AI generated images

Literature Review

Signals	Papers	Methodology	Classification accuracy
EEG	1. Duan et al. (2013) 2. Atkinson and Campos (2016) 3. Sha'abani et al. (2020)	SVMs with differential entropy features SVMs with time and frequency domain feature selection techniques. k-Nearest Neighbors (kNN)	83% 84% 83%
Physiol-ogical signals	1. Campanella et al. (2023) 2. Kaczor et al. (2020) 3. Cosoli et al. (2021)	SVMs with time and frequency domain feature selection techniques. kNN SVM or kNN	74.5% 70% 72.62% or 58.33%

Our innovation

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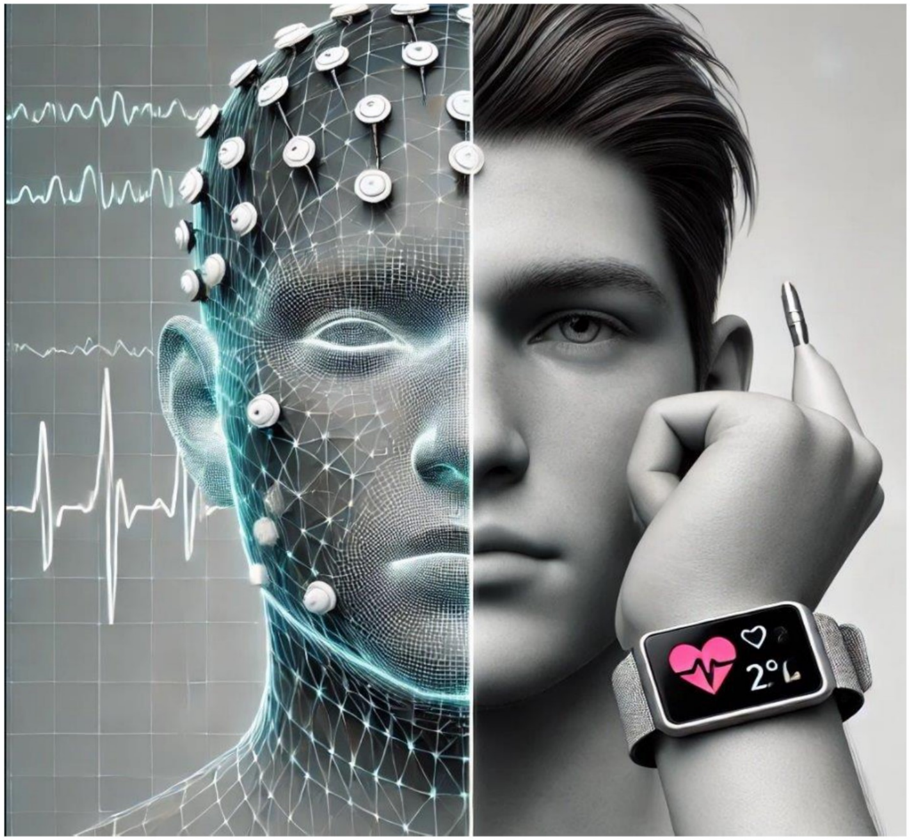
- The Challenge: Emotions are elusive. We seek to decode them using brain and physiological signals.

- Our Approach: Bridging the gap between emotion and technology by combining EEG brainwave signals and wristband data.

- Core Outcome: Classifying emotions - Excitement, Fear, Happiness, Relaxation, and Sadness.



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Overview – Today's Agenda

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Fundamentals

- Devices
- Valence Arousal Model
- Graphical User Interface (GUI)

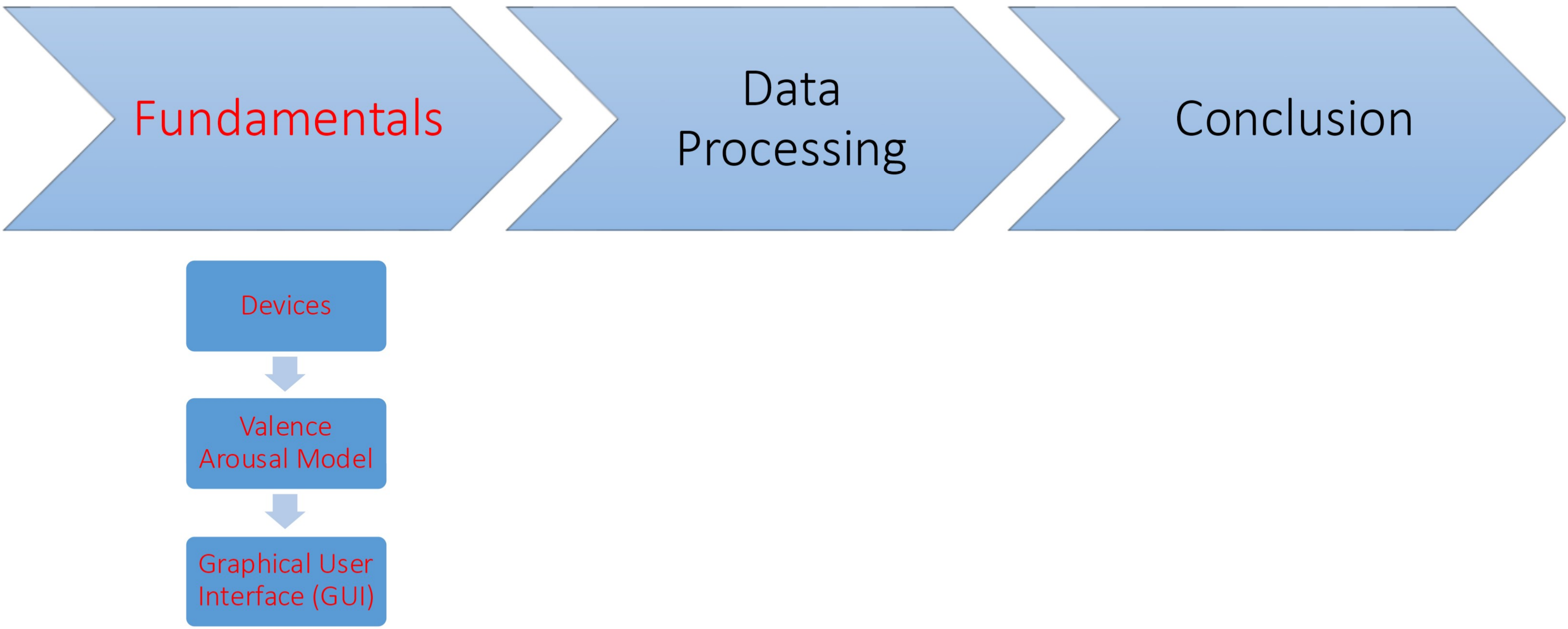
Data Processing

- Segmentation
- Feature Extraction
- Dimensionality Reduction
- Classification

Conclusion

- Evaluation
- Summary
- Future Work

1. Fundamentals

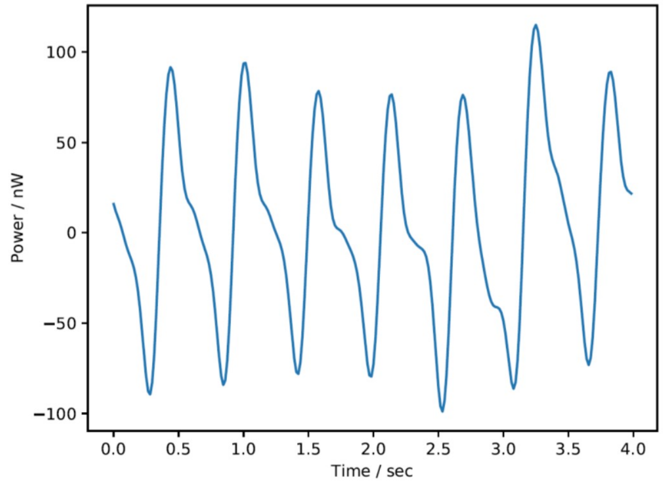


Emotiv EPOC Flex:

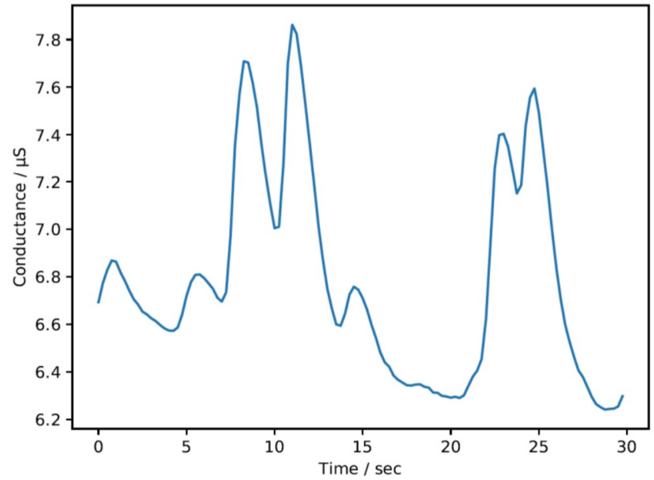
Aspect	Details
Channels	32 EEG channels, 2 reference channels (CMS and DRL)
Setup	Flexible sensor placement; using 10-20 international system
Sampling Rate	128 samples per second (128 Hz)

Fig: Emotiv EPOC Flex
Image source: Mindec store [Min23]

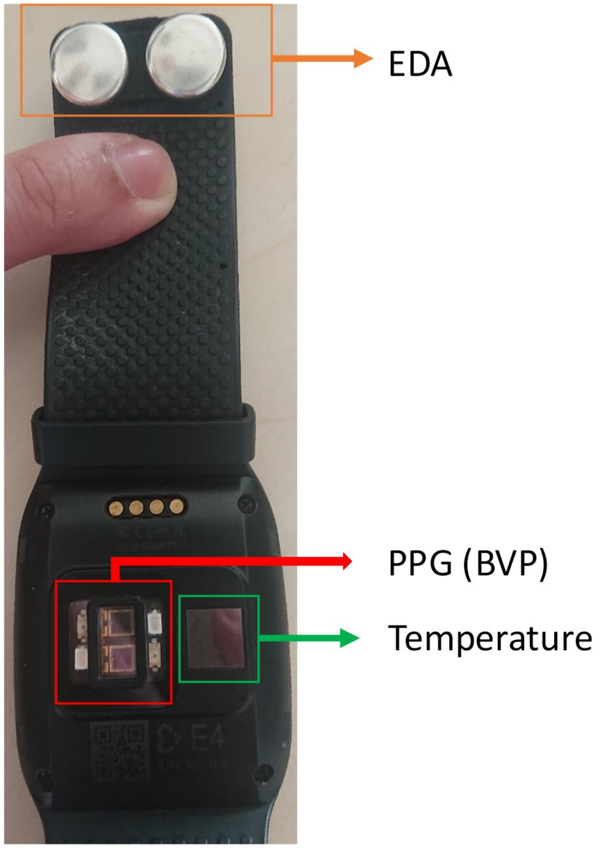
Empatica E4 wristband:



Blood Volume Pulse (BVP)



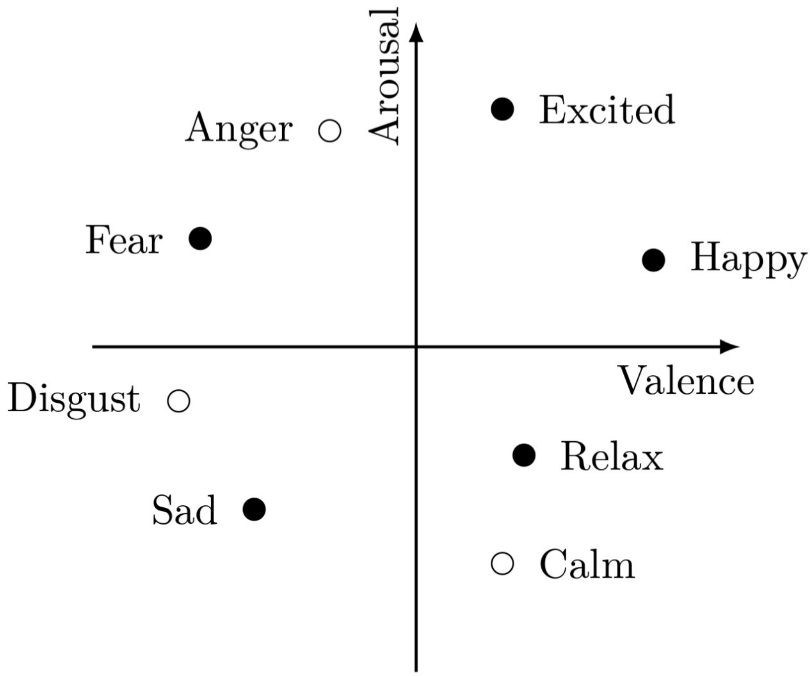
Electrodermal Activity (EDA)



- Simplified version with two axis

- Arousal: Intensity
- Valence: Pleasant

- Stimuli videos taken from DEAP dataset



1.3 Fundamentals – Graphical User Interface (GUI)

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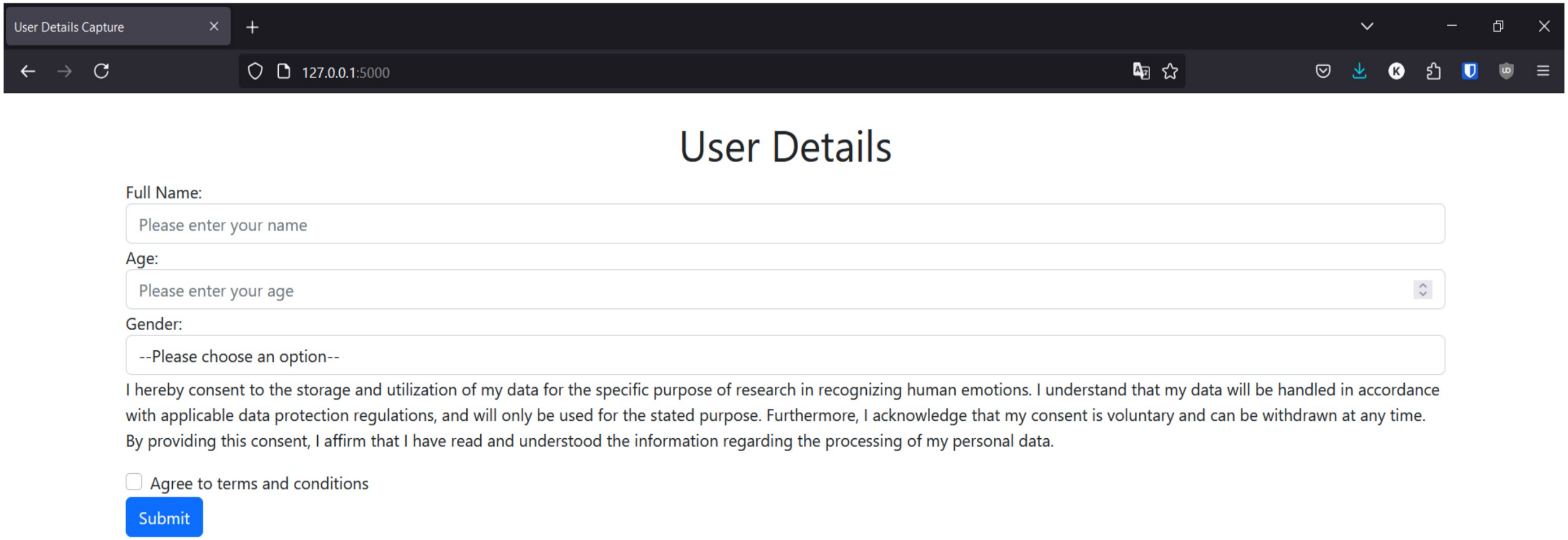
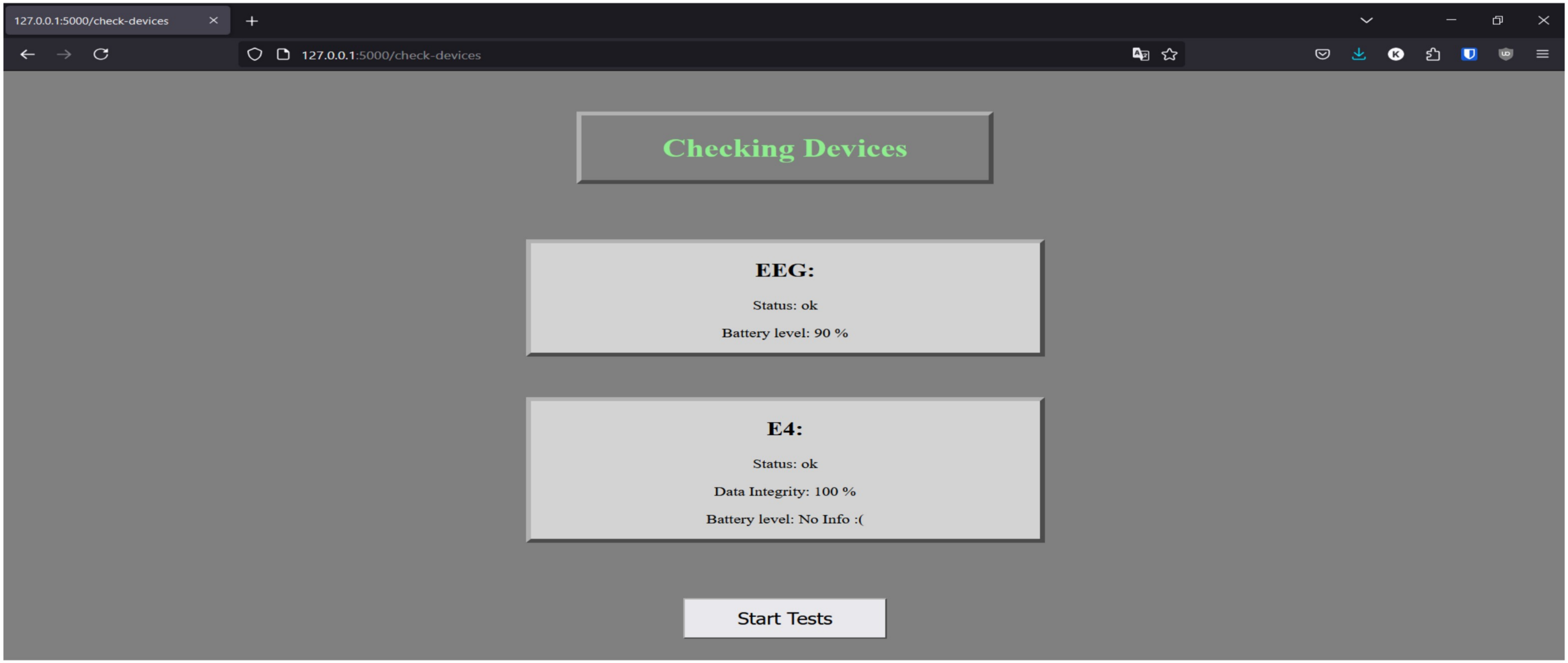
- Eases the data capture process.
- Developed as a web application using Python, Flask, MySQL, HTML, and CSS.

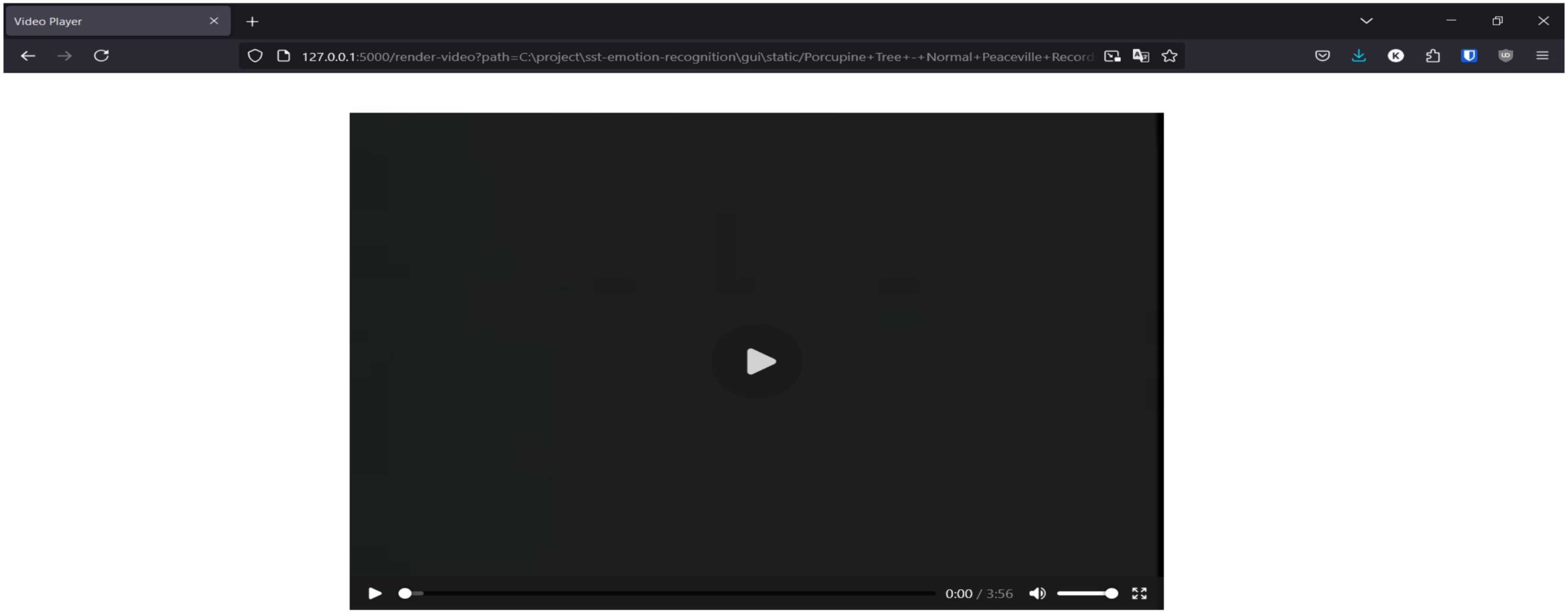


1.3 Fundamentals – Graphical User Interface (GUI)

- Integrated with the EEG and Wristband for seamless data capture.

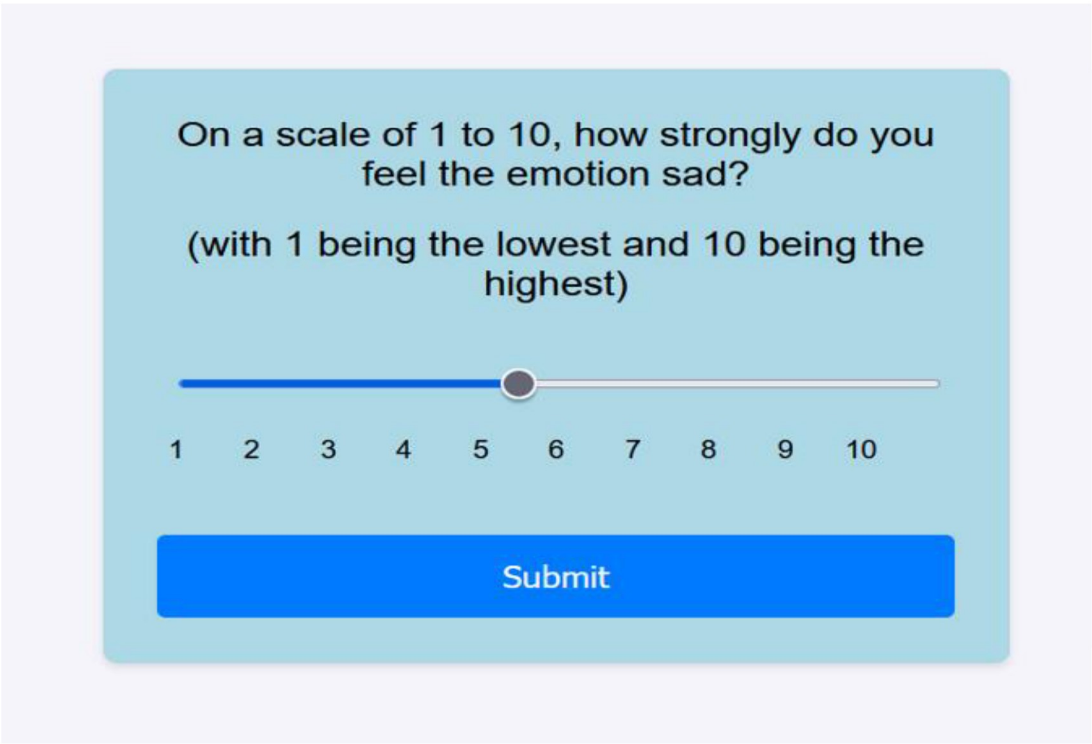


- Videos streamed from the DEAP dataset.



[DEAP] https://www.eecs.qmul.ac.uk/mmv/datasets/deap/

- Captures User feedback.
- Relax page with a timer



2. Data Processing

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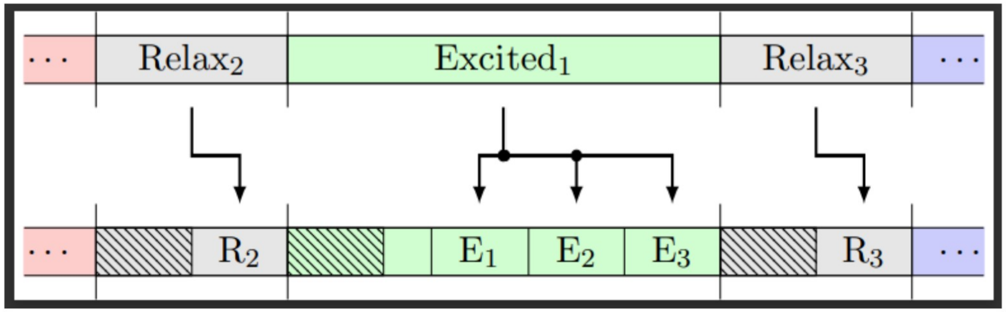
Fundamentals → Data Processing → Conclusion

- Segmentation
- Feature Extraction
- Dimensionality Reduction
- Classification

- Only cuts parts representing videos
- Start of each video might be influenced from previous video
  -> Cut start away
- Cutting initiates from the end of each video and yields segments of equal length



2.2. Feature Extraction – Signal Pre-processing

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- Feature Extraction: extracting representations from data that are well suited for the task of classifying emotions

- The types of features extracted can be classified broadly into two categories:
    - Time Domain
    - Frequency Domain

Pre-processing of WB and EEG signals:

Wristband	EEG
• BVP: Bandpass filter with cut-off frequencies 0.5 and 10 Hz • EDA: Raw EDA signal is split into it's 3 associated components i.e Tonic, Phasic and smna(using a 3rd party tool)	• Bandpass filter with cut-off frequencies 0.5 and 45 Hz for all channels

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[cvxEDA]: Greco, Alberto et al. “cvxEDA: A Convex Optimization Approach to Electrodermal Activity Processing.” *IEEE transactions on bio-medical engineering* vol. 63,4 (2016): 797-804. doi:10.1109/TBME.2015.2474131

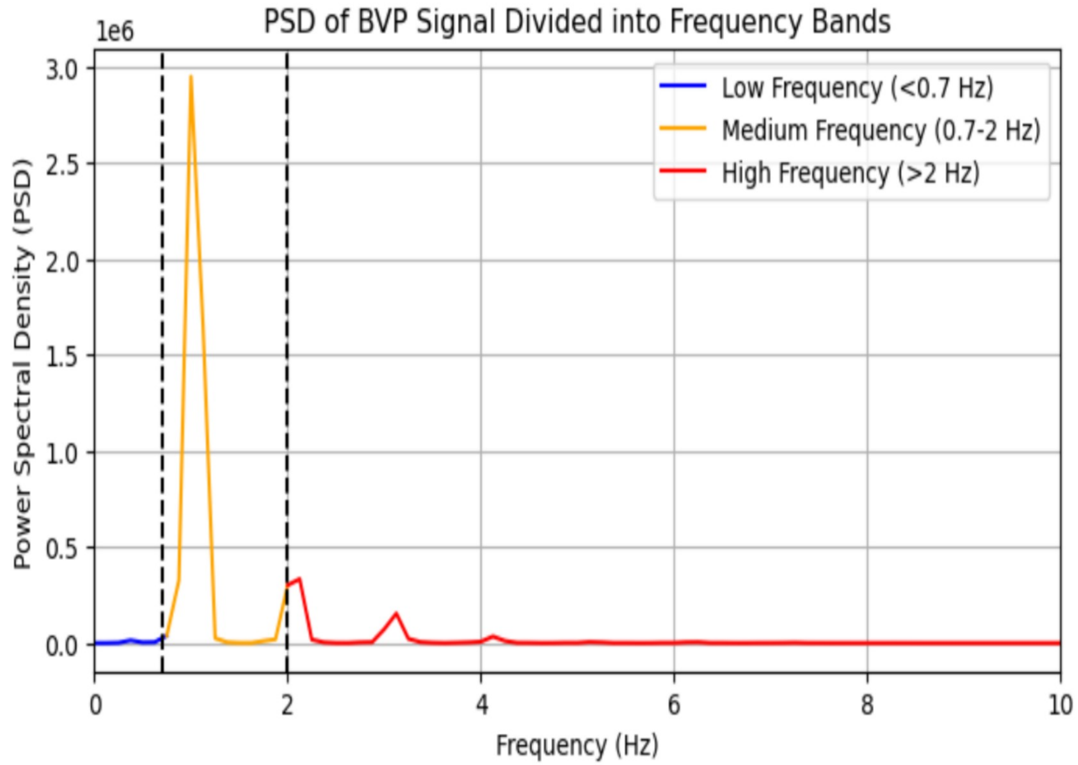
2.2. Feature Extraction – Time Domain Features

- Statistical features are computed for each segment of the data, for both the WB and EEG.

- The common features between both the devices are as follows:
  - Mean
  - Median
  - Variance
  - Skewness
  - Kurtosis
  - Inter-Quartile Range
  - ...

2.2. Feature Extraction – Frequency Domain Features

- Computing the Short-Time Fourier Transform(STFT).
- Computing the Power Spectral Density(PSD).
- Computing the Power Mean Value of different sub-bands.
- Computing the Fundamental Frequency.



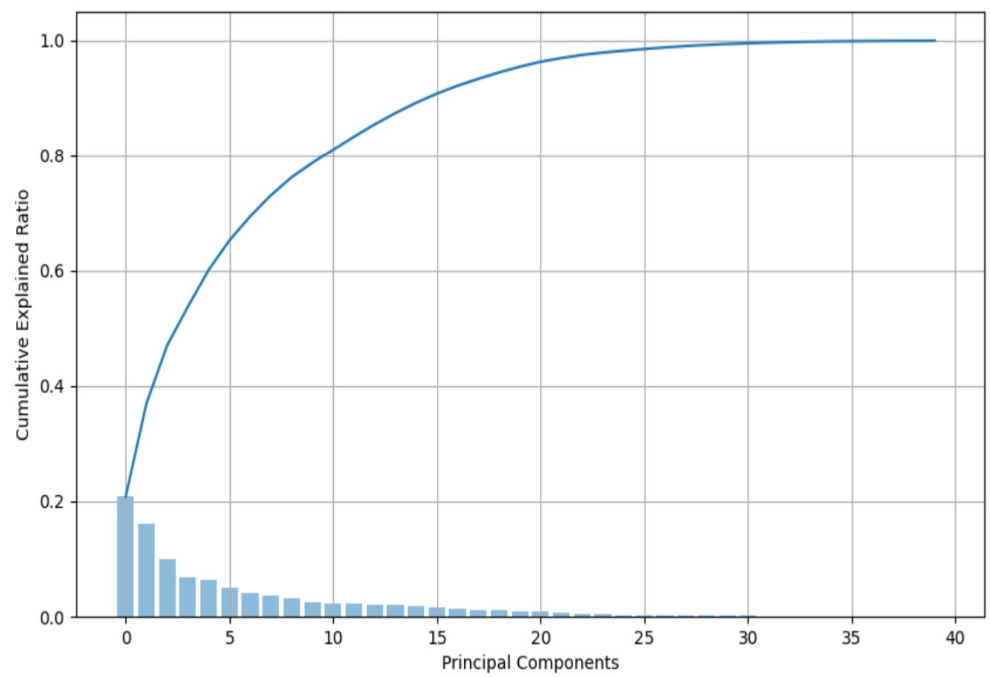
[ZWYG18] Emotionsense: Emotion recognition based on wearable wristband, 2018

- Unsupervised dimensionality reduction technique, which focuses on preserving the variance of the original data.
- The aim is to maximize variance w. the following constraint (for n=1 dim.)

$$\mathbf{u}_1{}^T \mathbf{S} \mathbf{u}_1 + \lambda \left(1 - \mathbf{u}_1^{\mathrm{T}} \mathbf{u}_1\right)$$

- Reduction in dimensions:
  - WB: 98 dim. to 6 dim.
  - EEG:551 dim. to 79 dim.

Elbow curve plot describing the Individual Explained Variance for all components



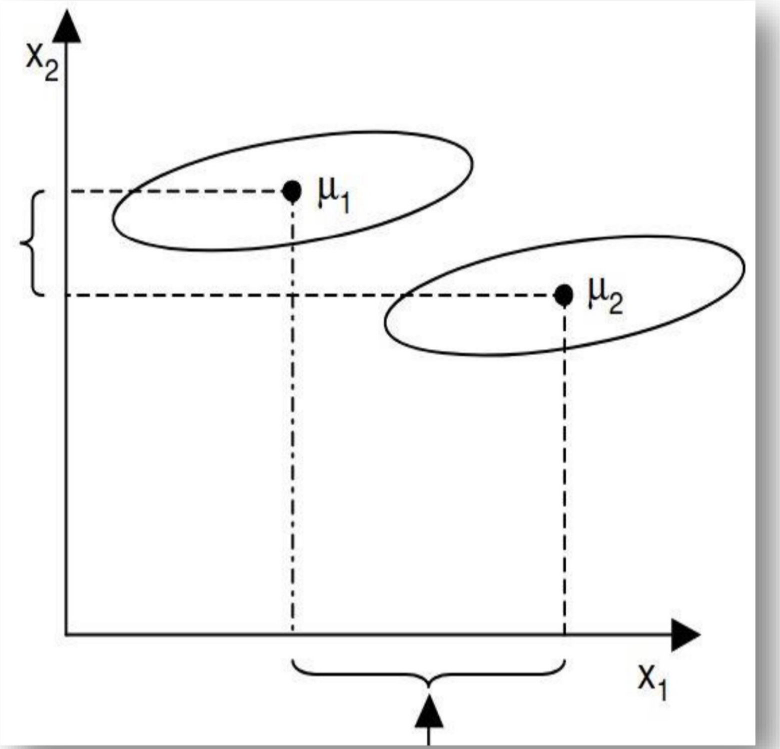
[TUB]https://www.tml.cs.unituebingen.de/teaching/2020_statistical_learning/downloads_free/luxburg_statistical_learning_slides.pdf

- Supervised
- Maximizes class separability
- 'C-1' number of linear discriminants

2-Class Problem:

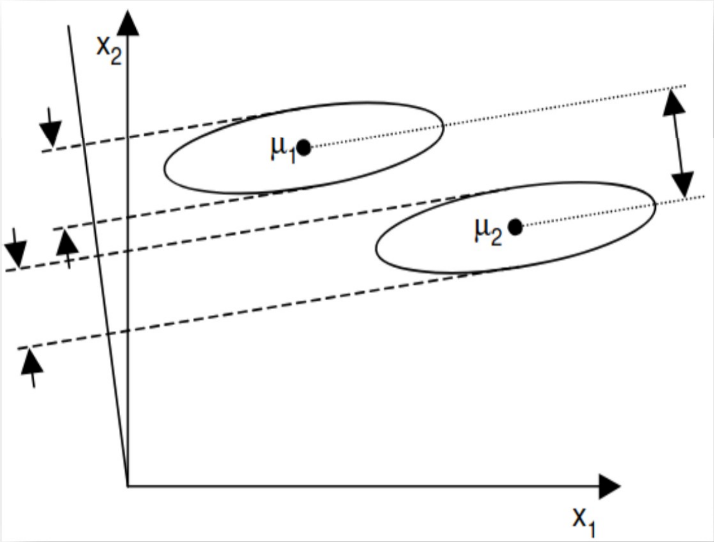
- Class Means: $$\mu_k = \frac{1}{N_k} \sum_{x_i \in C_k} x_i$$
- Objective function: $$J(w) = |\tilde{\mu}_1 - \tilde{\mu}_2| = |w^T(\mu_1 - \mu_2)|$$

❌ **Limitation**: Maximizing this distance alone is not enough



2.3. Dimensionality Reduction – LDA

- Within-class Scatter: $$S_W = \sum_{x \in C_1} (x-\mu_1)(x-\mu_1)^T + \sum_{x \in C_2} (x-\mu_2)(x-\mu_2)^T$$
- Between-class Scatter: $$S_B = \sum_{k=1}^{C} N_k(\mu_k-\mu)(\mu_k-\mu)^T$$
- Fisher criterion: $$J(w) = \frac{w^T S_B w}{w^T S_W w}$$



Figures source: R. Gutierrez, "CS790: Pattern Recognition," Texas A&M University, 2002. Available: https://people.engr.tamu.edu/rgutier/web_courses/cs790_w02/l6.pdf

2.4. Classifiers – k-Nearest Neighbors (kNN)

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- Non-parametric method.
- Classifies based on nearest 'k' neighbors.
- Majority voting.

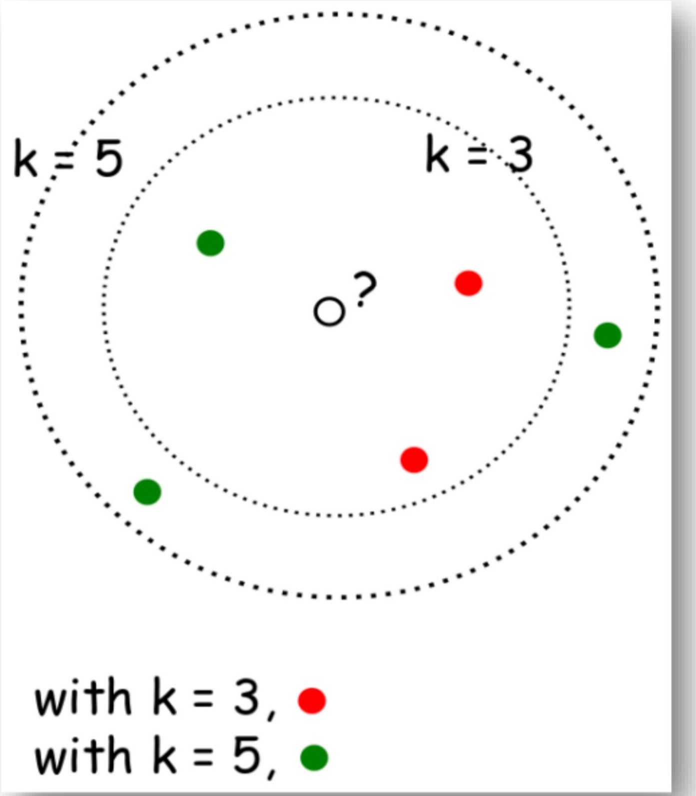
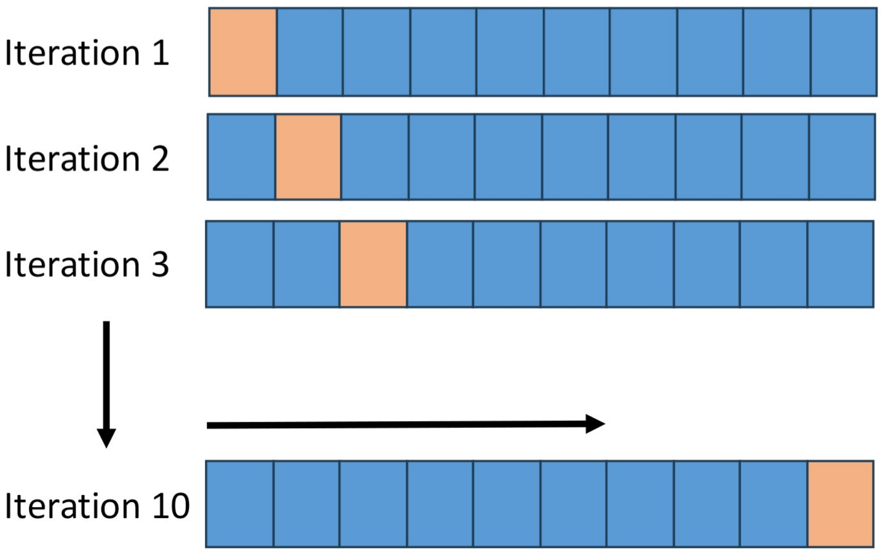
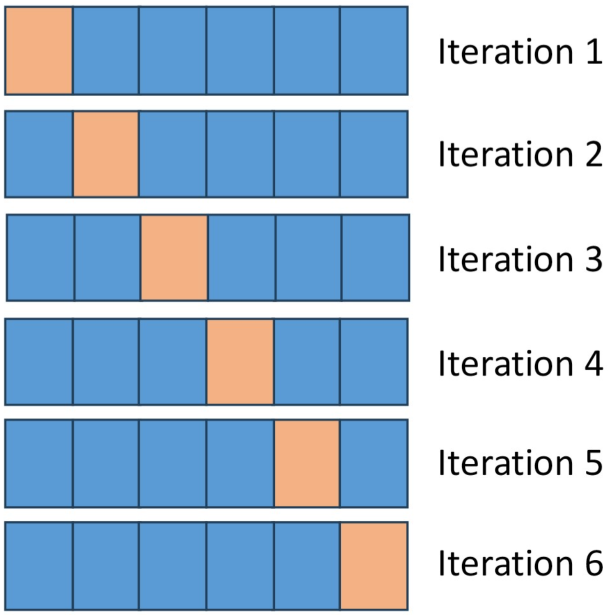


Image source: Towards Data Science, "k-Nearest Neighbors in Python," towardsdatascience.com.

i. **Stratified 10-Fold**



ii. **Leave-One-Out**

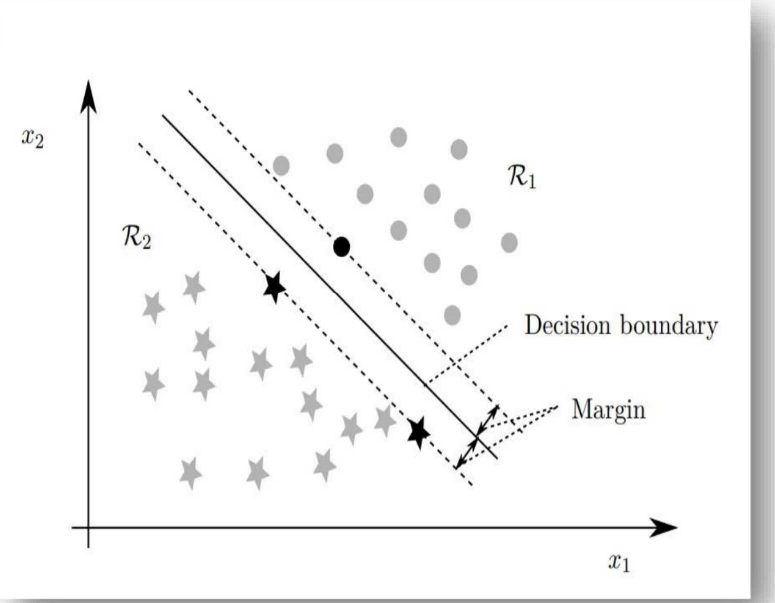


T.-T. Wong, "Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation," Expert Syst. Appl., vol. 42, pp. 1796–1808, 2015.

An algorithm that finds the optimal hyperplane separating different classes.

The objective function is to maximize the margin and minimize the classification error.

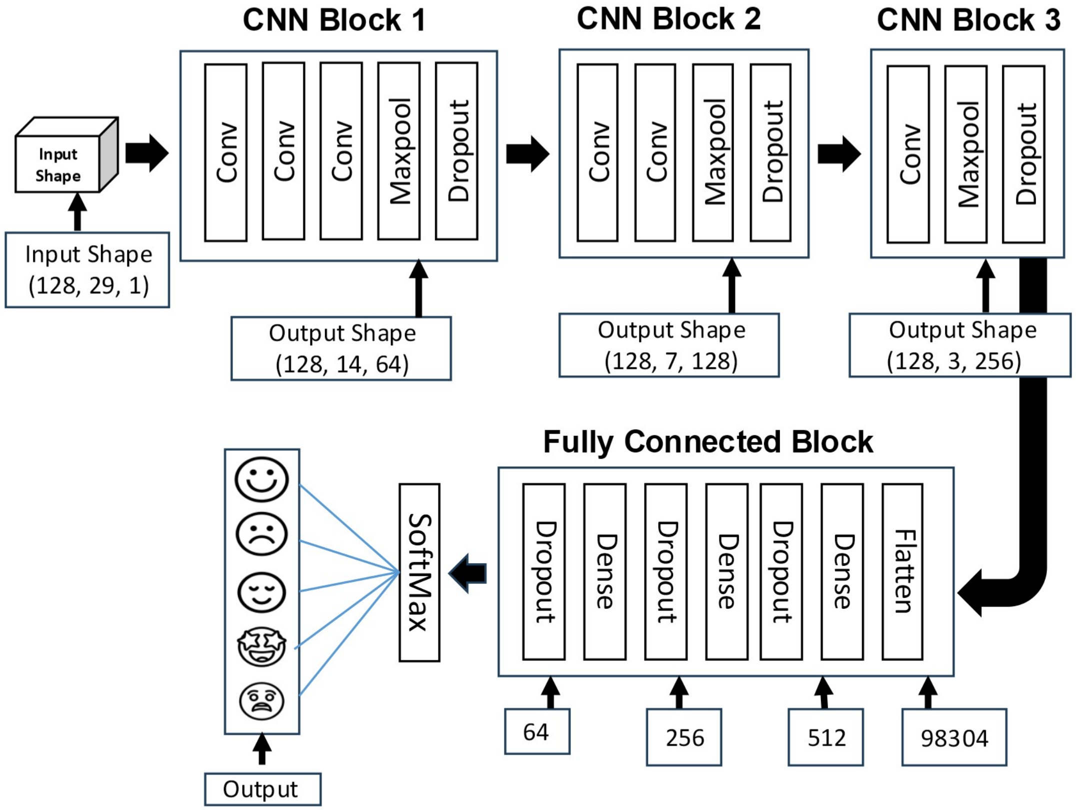
$$\text{minimize } \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{n}\xi_i,$$



C controls trade-off between maximizing margin and classification Error.
Kernal trick allows SVM to handle non-linear data in higher dimension.

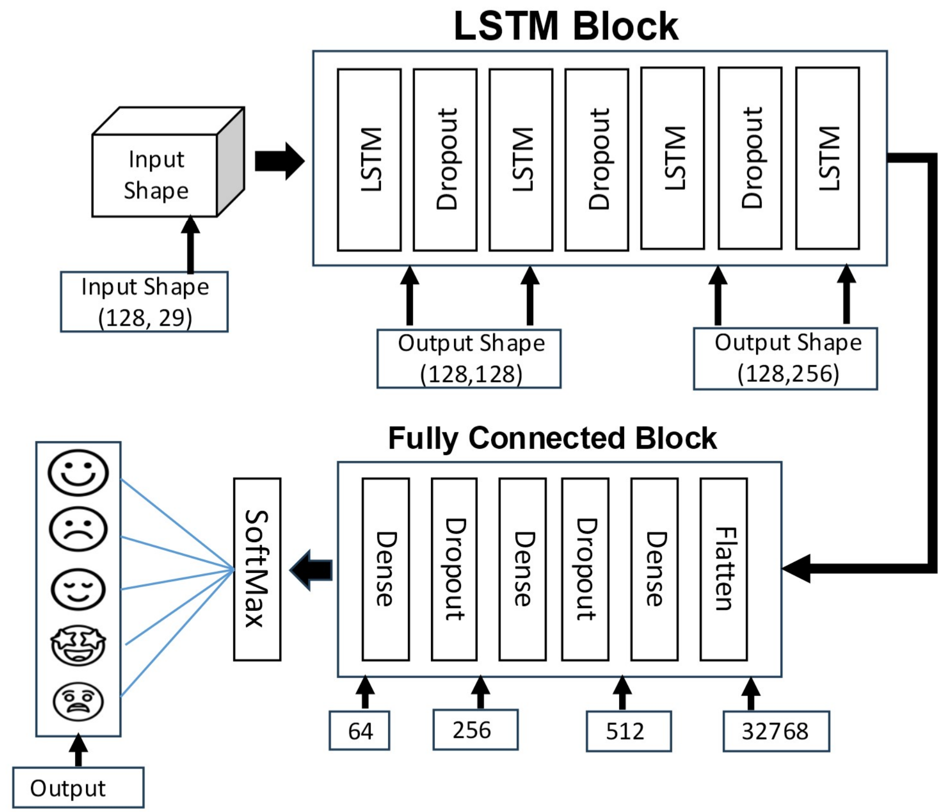
2.4. Classifiers - CNN Model

- CNN captures spatial patterns across time in the data.
- CNN helps in Capturing local patterns in data.



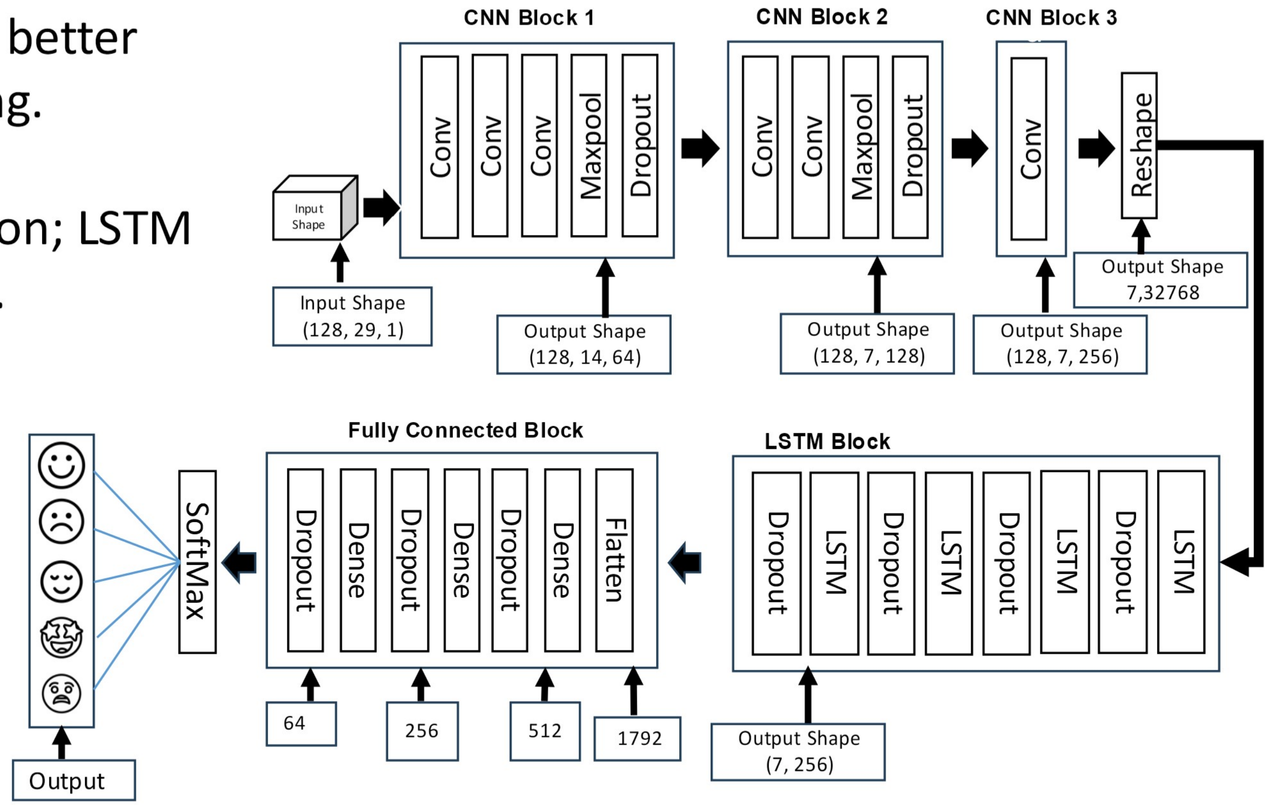
Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-022-12310-7

- LSTM learns time-based dependencies.
- It captures long-term patterns over time.
- LSTM excels in recognizing temporal emotional patterns.



Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-022-12310-7

- Combines CNN and LSTM for better feature and sequence learning.
- CNN handles feature extraction; LSTM manages time dependencies.



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2.4. Classifiers - Ensemble

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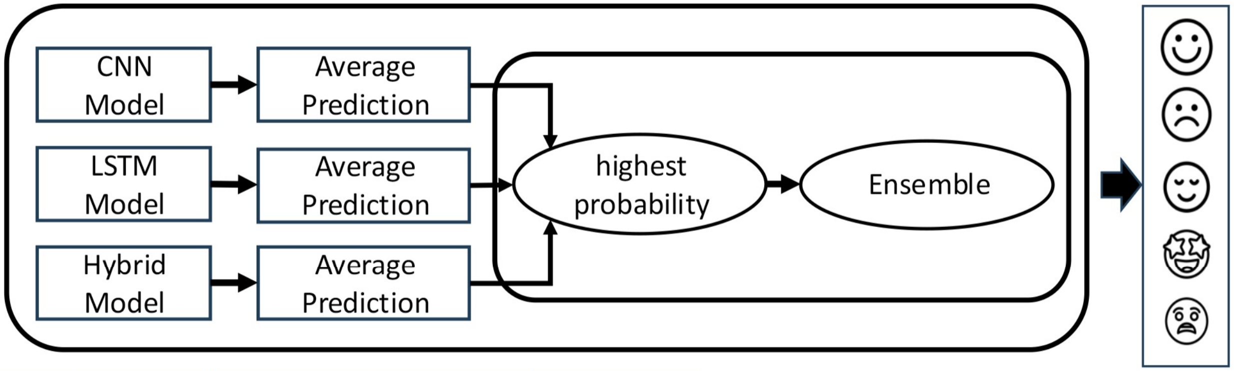

Model	Happy	Sad	Fear	Relaxed	Excited
CNN	0.12	0.35	0.33	0.45	0.35
LSTM	0.21	0.14	0.15	0.35	0.25
Hybrid	0.15	0.55	0.23	0.55	0.15
Average Prediction/3	0.16	0.34	0.23	0.45	0.25

Final prediction: **Relaxed** (since it has the highest average probability of 0.45)

- Merges predictions from CNN, LSTM, and Hybrid models.
- Aggregates strengths of multiple models for robust results.
- Ensemble increases accuracy.

Iyer, A., Das, S. S., Teotia, R., Maheshwari, S., & Sharma, R. (2022). CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-022-12310-7

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Fundamentals

Data Processing

Conclusion

Evaluation

Summary

Future Work

3.1. Evaluation of classification using WB data

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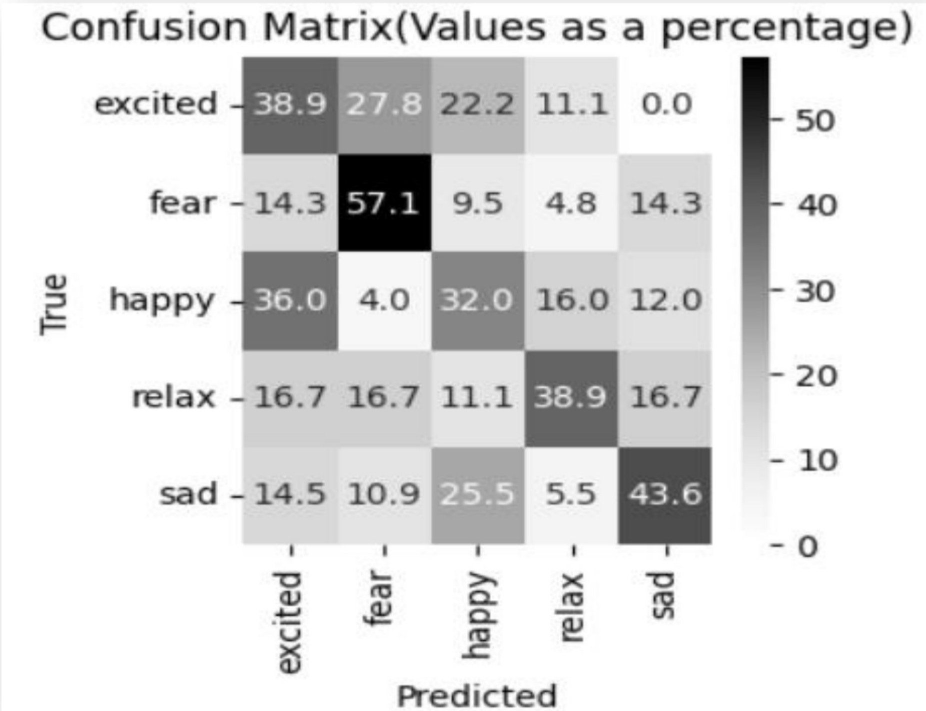
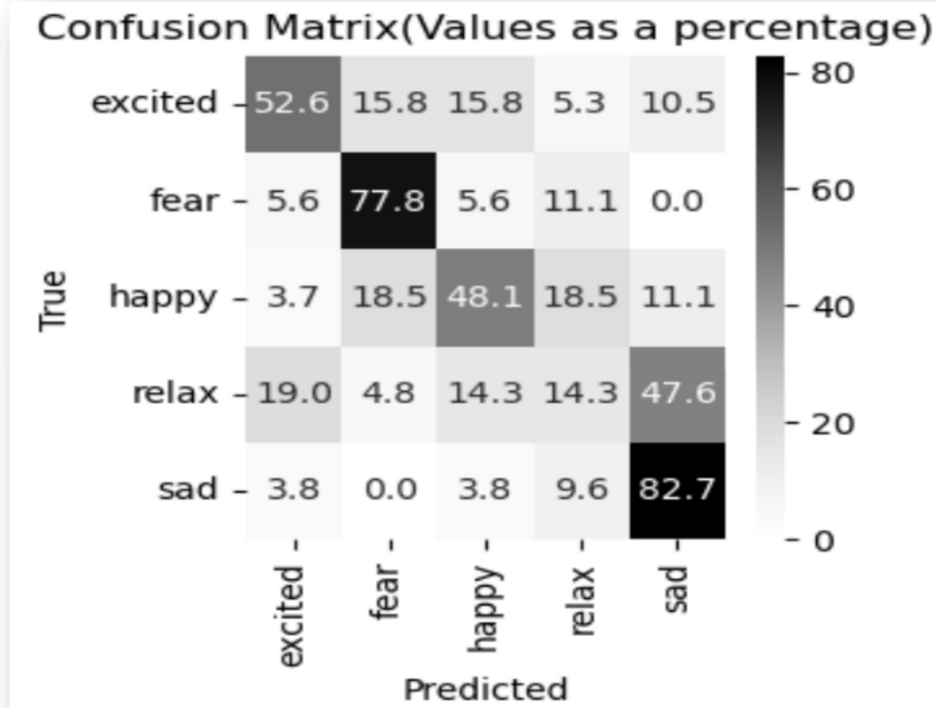
- The zero rate Classifier was used as the baseline, resulting in a baseline of 37.96%.
- The highest accuracy of 60.58% was achieved using the wrist band for the frequency feature set with an SVM classifier.
- The best accuracy for the KNN of 45.55% was achieved on the combined feature set.

Feature Set	**SVM+LDA(%)**	**KNN+PCA(%)**
Frequency	**60.58**	27.13
Time	33.58	40.27
Combined	37.23	**45.55**

3.1. Evaluation of classification using WB data



KNN(Combined)



SVM(Frequency)

3.1. Evaluation of EEG data classification

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- Chance level accuracy for 5 classes: 20%.
- DNN, SVM, kNN used both statistical and freq. features.
- Highest accuracy: Ensemble classifier 85%.

Classifier	**Test Accuracy (%)**
Ensemble (CNN + LSTM + Hybrid)	**85**
LSTM	83
CNN	82
DNN	80
SVM	79.5
Hybrid (CNN + LSTM)	77
kNN	62

3.2. Conclusion - Summary

- An approach aiming for emotion recognition was developed
- Musical videos were used as stimuli
- Automated recording of both EEG and WB data
- Data from each device was processed separately
- **EEG** data was preprocessed by filtering, windowing and features were extracted
  - Best classifier (ensemble) achieved 85% accuracy
- **WB** data was processed by segmentation, time and frequency features extracted
  - Best classifier (SVM) achieved 60.6%

3.3. Conclusion – Future Work

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- Combine multiple devices and compare to single solutions.
- Use more emotions for finer granularity (boredom, disgust, ...).
- Develop a real time approach.

Thank you!

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Questions?

References

- [Min23] Mindtec Store. Emotiv epoc flex saline sensor set, 2023.
- [DEAP] https://www.eecs.qmul.ac.uk/mmv/datasets/deap/
- [ZWYG18] Emotionsense: Emotion recognition based on wearable wristband, 2018
- [Iyer22] CNN and LSTM based Ensemble Learning for Human Emotion Recognition using EEG Recordings, 2022.
- [TUB] https://www.tml.cs.uni-tuebingen.de/teaching/2020_statistical_learning/downloads_free/luxburg_statistical_learning_slides.pdf
- [CvxEDA] Greco, Alberto et al. "cvxEDA: A Convex Optimization Approach to Electrodermal Activity Processing." *IEEE transactions on bio-medical engineering* vol. 63,4 (2016): 797-804. doi:10.1109/TBME.2015.2474131