**Research paper Take aways**

**Paper 1: Detection of mental fatigue state with wearable ECG devices**

**Introduction**

* Overwork-related disorders like CCVD and mental disorders are significant global health issues.
* "Karoshi," meaning death by overwork, highlights Japan's intense work culture.
* Miwa Sado, a journalist, died after logging 159 hours of overtime in one month.
* Approximately 600,000 deaths in China annually are attributed to overwork.
* Mental fatigue, a subjective feeling, is a better indicator of overwork than hours worked.
* Long working hours lead to stress, accidents, absenteeism, and reduced productivity.
* Real-time monitoring of mental fatigue using wearable devices is crucial.
* Current measures for mental fatigue include subjective self-reports and objective performance tasks.
* EEG is commonly used for measuring mental fatigue, but it is cumbersome for daily use.
* Wearable smart devices, like ECGs, are emerging for real-time health monitoring.
* The study aims to explore if mental fatigue can be detected using wearable ECG devices.

**The devices**

* Data from the wearable ECG device is transmitted to a smartphone via Bluetooth.

**Experimental design**

* 35 healthy participants from a public university in East China were recruited.
* Subjects with overwork-related issues were excluded to ensure accurate fatigue manipulation.
* A quiz was used to induce fatigue, with data collected before and after.
* Participants completed the Chalder Fatigue Scale questionnaire before and after the quiz.
* The quiz included 55 questions covering various cognitive tasks.
* Participants were incentivized with a cash bonus for participation.
* Institutional review board approval was obtained for the study.

**Data preprocessing**

* ECG signals were recorded to extract heart rate variability (HRV) indicators.
* HRV measures the variation in time intervals between heartbeats, indicating nervous system regulation.
* Time domain indicators included NN.mean, SDNN, rMSSD, and PNN50.
* Frequency domain indicators included TP, HF, LF, and VLF.
* ECG data were collected every 0.004 seconds, with a sample rate of 250 Hz.
* 29 out of 35 subjects were qualified for analysis after excluding outliers.
* HRV indicators were calculated for both pre-quiz and post-quiz states.
* Self-reported fatigue was measured using a binary variable based on the Chalder Fatigue Scale.

**Feature selection**

* The most salient HRV indicators were selected to distinguish fatigue states.
* Feature selection aimed to simplify the model, reduce variance, and lower computational costs.
* Random forest method was used to identify important HRV indicators.
* MDA and MDG scores were calculated to evaluate variable importance.
* Six indicators (NN.mean, PNN50, rMSSD, TP, LF, VLF) were retained for further analysis.

**Machine learning performance**

* Four algorithms (SVM, KNN, NB, LR) were used to classify fatigue states based on HRV indicators.
* KNN achieved the best performance with a CV accuracy of 75.5%.
* The study evaluated the importance of different feature combinations for predicting fatigue.
* The optimal number of indicators for best performance was found to be two or three.

**Principal results**

* Mental fatigue can be detected with reasonable accuracy using a wearable ECG device.
* Key HRV indicators for detection include NN.mean, PNN50, TP, and LF.
* KNN outperformed other algorithms, making it a promising approach for fatigue detection.

**Comparison with prior work**

* Previous studies have explored ECG signals for fatigue detection but focused on different contexts.
* This study found specific HRV indicators associated with mental fatigue due to overwork.
* The results support the idea that combinations of indicators improve classification accuracy.

**Conclusion**

* The study successfully demonstrated the potential of wearable ECG devices for detecting mental fatigue.
* KNN was the most effective algorithm, achieving a CV accuracy of 75.5%.
* Limitations include a small sample size and the need for validation in real-world settings.
* Future research should explore the approach in diverse populations and conditions.

**Paper 2: The Effect of Mental States on Blood Pressure and Electrocardiogram**

**The document, *The Effect of Mental States on Blood Pressure and Electrocardiogram*, examines how different mental states affect blood pressure (BP) and electrocardiogram (ECG) readings. Here’s a summary of the key points:**

* **Objective: The study investigates physiological changes in BP and ECG during cognitive activities categorized as Motor Action (MA), Thoughts (TH), Memory Related (MR), and Emotions (EM).**
* **Methodology:**
  + **The experiment involved 11 healthy undergraduate and postgraduate students.**
  + **BP and ECG measurements were conducted using the BIOPAC system.**
  + **Subjects performed specific cognitive tasks designed to induce particular mental states.**
  + **Fast Fourier Transform (FFT) and smoothing techniques were applied to analyze signals.**
* **Findings:**
  + **BP showed significant changes during MA and TH tasks but remained largely unchanged in MR and EM tasks.**
  + **ECG displayed significant variations in MR and EM tasks but showed no substantial changes during MA and TH tasks.**
  + **Mental stress induced cardiovascular responses, affecting ECG frequency values.**
  + **BP levels varied depending on the nature and complexity of cognitive tasks.**
* **Applications & Future Work:**
  + **The research provides a method to classify mental states based on BP and ECG data.**
  + **Future studies aim to integrate additional physiological measures like EEG and Galvanic Skin Response (GSR).**
  + **Insights from this research could contribute to adaptive interface designs to assist disabled or elderly individuals.**

**Paper 3: ECG Pattern Analysis for Emotion Detection**

**Detailed Summary of the Paper**

**The paper "ECG Pattern Analysis for Emotion Detection" by Foteini Agrafioti, Dimitrios Hatzinakos, and Adam K. Anderson, published in IEEE Transactions on Affective Computing (2012), investigates how Electrocardiogram (ECG) signals can be leveraged for emotion recognition.**

**This study acknowledges that traditional behavioral modalities (facial expressions, vocal traits) are prone to voluntary suppression, while physiological signals like ECG offer more objective emotional assessments. The authors argue that ECG-based emotion recognition should be subject-dependent, as ECG signals contain biometric-specific properties.**

**The study introduces Empirical Mode Decomposition (EMD) as a method to extract emotion-related features from ECG signals dynamically. The authors compare active vs. passive emotion induction, demonstrating that active induction produces stronger ECG reactivity.**

**Q1: What is the paper talking about?**

**This paper explores the capabilities and limitations of using ECG signals for emotion detection. The authors emphasize that ECG is inherently a biometric trait, meaning that emotion classification should be individualized rather than universal.**

**The methodology involves using EMD and Hilbert-Huang Transform (HHT) to analyze instantaneous frequency components in ECG signals and detect emotional states. The study also introduces two experimental setups:**

1. **Active arousal induction (direct interaction with stimuli)**
2. **Passive arousal/valence induction (viewing affective media)**

**Results indicate higher ECG responsiveness when the emotion stimulus is actively induced, supporting the argument that subject-dependent recognition models work best for ECG-based emotion detection.**

**Q2: What are the emotions classified and how are they classified?**

**The paper follows Affective Dimensional Models (ADM) to classify emotions based on arousal and valence:**

* **Arousal: Measures emotional intensity (low to high).**
* **Valence: Measures emotional pleasantness (positive to negative).**

**Instead of discrete emotions (joy, fear, anger), the authors map emotions into a 2D space (AV plane), where classification occurs based on ECG signal variability.**

**Two separate classification tests were conducted:**

1. **Arousal differentiation (low vs. high emotional intensity).**
2. **Valence detection (positive vs. negative emotional response).**

**ECG signal frequency and amplitude were analyzed in both cases to extract relevant emotional features.**

**Q3: How are emotions extracted or identified from ECG signals?**

**Emotion recognition relies on analyzing frequency variations and waveform changes in ECG signals.**

**The process includes:**

1. **Empirical Mode Decomposition (EMD): Decomposes ECG signals into Intrinsic Mode Functions (IMFs).**
2. **Hilbert-Huang Transform (HHT): Helps analyze instantaneous frequency variations of ECG waves.**
3. **Baseline ECG subtraction: Emotional state is detected as a variation from the subject’s normal ECG rhythm.**

**These ECG features (amplitude shifts, oscillations, frequency patterns) indicate whether the subject is experiencing a particular emotional state.**

**Q4: Preprocessing of ECG Signals (In Detail)**

**To ensure accurate emotion detection, ECG signals undergo comprehensive preprocessing, including:**

* **Noise reduction: Eliminating physiological artifacts caused by breathing, muscle movements, and external disturbances.**
* **Fiducial point detection: Locating P, QRS, and T waves using empirical localization rules.**
* **Synthetic ECG generation: A standard ECG signal is created for comparative analysis across different emotional states.**
* **Baseline adjustment: Normal ECG data is subtracted from experimental ECG signals to detect emotion-related fluctuations.**

**These preprocessing steps ensure consistency before applying EMD and HHT for feature extraction.**

**Q5: Features of ECG Signals Used to Train the Model**

**The study extracts specific ECG-based features that indicate emotional arousal and valence:**

* **Heart rate variability (HRV) changes**
* **Amplitude variations in QRS and T waves**
* **Instantaneous frequency components (HHT output)**
* **Oscillatory activity within intrinsic mode functions (IMFs)**

**Each feature is selected based on its sensitivity to emotional stimuli, ensuring optimal classification accuracy.**

**Q6: Machine Learning Model Used & Dataset (Very Important)**

* **Machine Learning Approach: The paper does not use traditional ML classifiers like SVM or neural networks. Instead, it relies on EMD and HHT-based classification, designed to work on a per-subject basis.**
* **Dataset: The ECG recordings used for training come from 44 subjects, exposed to active vs. passive emotional stimuli.**
* **Training Methodology:**
  + **Feature Selection: Fisher Projection (FP) & Sequential Floating Forward Search (SFFS) were applied.**
  + **Subject-specific classification: Each individual’s ECG baseline was used as a reference to detect emotion-related changes.**

**Unlike generic ML models, this approach recognizes the subject-specific nature of ECG signals and applies personalized classification models.**

**Q7: Results Obtained & Actual Outcome**

* **Valence classification accuracy: Up to 89% in experiments.**
* **Better performance with active stimuli compared to passive emotion induction.**
* **ECG reactivity stronger in cases where emotions are actively triggered.**
* **Subject-specific classifiers were more effective than universal models.**

**These findings support the argument that ECG-based emotion recognition should be personalized.**

**Q8: Limitations Identified**

* **Subject variability: ECG features vary significantly from person to person, limiting generalizability.**
* **Experimental constraints: Emotions induced in controlled lab conditions may differ from real-world emotional responses.**
* **Potential misclassifications: Signal noise and artifacts can disrupt feature extraction.**
* **Absence of multimodal fusion: The study does not integrate other biosignals (EEG, GSR, etc.) to improve detection accuracy.**

**Q9: Research Gap (Most Important)**

**The research has several gaps that future studies should address:**

1. **Lack of deep learning models: Modern DL techniques could improve feature extraction and classification accuracy.**
2. **Small dataset: Only 44 subjects were used; larger datasets with diverse demographics would enhance generalizability.**
3. **No multimodal fusion: ECG is not combined with EEG, GSR, or other biosignals, which might improve performance.**
4. **Limited subject-independent testing: Although subject-specific models perform well, real-world applications require generalized models.**

**Paper 4: ECG-based Emotion Recognition: Overview of Methods and Applications**

**Summary of the Paper**

The paper explores recent advancements in ECG-based emotion recognition, emphasizing the methods used to process ECG signals and classify emotional states. It discusses major challenges in affective computing, including inter-subject variability and the presence of noise in ECG data. The authors provide an overview of various feature extraction techniques, machine learning models, and practical applications in medicine, marketing, and driver monitoring. They also highlight the importance of combining ECG signals with other physiological signals or facial expression recognition for better accuracy.

**1. What is the paper talking about?**

The paper discusses how electrocardiogram (ECG) signals can be used for emotion recognition, detailing methodologies applied to extract useful features, train machine learning models, and classify emotions. The study emphasizes challenges such as inter-subject variability and noise interference, showcasing different approaches taken by researchers to improve accuracy. Furthermore, it explores practical applications in domains like healthcare, smart cars, and intelligent human-machine interfaces.

**2. What are the emotions classified, and how are they classified?**

The paper primarily focuses on recognizing basic human emotions, including:

Joy  
Sadness  
Anger  
Fear  
Happiness  
Disgust  
Neutral

**Classification Methods:**

* Binary classification: Some studies classify two emotions (e.g., Joy vs. Sadness).
* Multi-class classification: Others aim to recognize multiple emotions (e.g., Joy, Anger, and Sadness).
* Feature extraction: Signals undergo wavelet transformations (DWT, CWT) to extract key features.
* Machine learning models: Common classifiers include K-Nearest Neighbor (KNN), Fisher classifiers, Support Vector Machines (SVM), and Neural Networks.

**3. How are emotions extracted or identified from the obtained ECG signals?**

Steps involved:

* ECG Signal Acquisition: Electrodes capture electrical signals from the heart.
* Preprocessing: Signals undergo noise filtering and segmentation.
* Feature Extraction: Relevant features are derived (e.g., heart rate variability, P-QRS-T wave analysis).
* Classification: Machine learning models map features to emotional states.
* Validation: Accuracy is tested using datasets and performance metrics.

Some methods, such as wavelet transformations and deep learning approaches, allow for more refined emotion classification.

**4. Preprocessing of ECG Signals (Detailed Explanation)**

Preprocessing is a crucial step to eliminate unwanted noise and artifacts. It involves:

* Filtering: Butterworth filters remove baseline wandering and noise.
* Normalization: Standardization ensures signals are within a fixed range.
* Segmentation: Signals are divided into meaningful windows (e.g., heartbeat cycles).
* Peak Detection: Identifying P-QRS-T waves for feature extraction.

Advanced preprocessing techniques such as Pan-Tompkins algorithm enhance the accuracy of extracted features.

**5. Features of ECG Signals Used to Train the Model**

Key features extracted from ECG signals include:

* Heart Rate Variability (HRV): Measures fluctuation between heartbeats.
* Time Domain Features: Includes RR intervals, P-P, T-T wave analysis.
* Frequency Domain Features: Extracted using Fast Fourier Transform (FFT).
* Wavelet Features: Discrete Wavelet Transform (DWT) applied for feature representation.
* Local Pattern Description (LPD): Features derived using Local Binary Pattern (LBP) and Local Ternary Pattern (LTP).

Feature selection techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) refine features for better classification accuracy.

**6. ML Model Used, Dataset, and Training Process**

* Machine Learning Models Explored:
* K-Nearest Neighbor (KNN)
* Fisher Classifier
* Support Vector Machine (SVM)
* Probabilistic Neural Network (PNN)
* Deep Learning (CNN, RNN, Fully Connected Layers)

**Dataset Information:**

1. ECG signals were acquired using 3 electrodes placed on subjects.
2. Emotion Induction: Video clips triggered emotions in subjects.
3. Data Processing: Signals were filtered using Butterworth filters.
4. Feature Extraction: Wavelet transformations applied for statistical features.
5. Training: 10-fold cross-validation was applied to train models.
6. Models like KNN and LDA showed the highest classification accuracy.

**7. Results Obtained and Actual Outcome**

**Key Findings:**

Binary classification accuracy: Joy – 92.1%, Sadness – 100%

Multi-class classification accuracy: Joy – 85.75%, Anger – 82.75%, Sadness – 95.25%

Best-performing classifier: Fisher-KNN classifier outperformed basic KNN models.

Deep Learning Approaches: Achieved high accuracy for subject-dependent recognition.

**Overall Outcome:**

ECG-based emotion recognition is highly promising, especially when combined with other physiological signals like EEG and Galvanic Skin Response (GSR).

**8. Limitations Found**

Despite promising results, several challenges remain:

* Inter-subject variability: ECG signals differ between individuals, making universal models difficult.
* Noise Sensitivity: ECG recordings are prone to interference.
* Limited Emotional Categories: Many studies focus on basic emotions (Joy, Sadness) rather than complex emotions.
* Dataset Constraints: Small sample sizes affect model generalization.
* Real-world Implementation Challenges: Requires wearable and portable devices for non-invasive emotion monitoring.

**9. Research Gap of this Paper (Most Important)**

**Unaddressed Areas:**

* Integration with Multimodal Data: The paper suggests combining ECG with facial expression recognition but does not explore deep multimodal fusion.
* Dynamic Emotion Recognition: Emotions fluctuate over time, but most models focus on static classifications rather than real-time monitoring.
* Personalized Emotion Models: Current models lack adaptability for individual-specific emotional variations.
* Use of Deep Learning Architectures: While neural networks are explored, end-to-end deep learning approaches for feature extraction need further study.
* Real-World Usability: Implementation in wearable devices or real-time applications (like smart cars or healthcare monitoring) is not extensively researched.

Future studies could focus on hybrid models, larger datasets, and robust validation techniques

**Paper 5: Novel multimodal emotion detection method using Electroencephalogram and Electrocardiogram signals**

**1. What is the paper talking about?**

The paper presents a multimodal emotion detection system that integrates Electroencephalogram (EEG), Electrocardiogram (ECG), and Photoplethysmography (PPG) signals to classify emotions evoked by video stimuli. The study focuses on improving emotion recognition accuracy by addressing challenges in EEG data, particularly eye blink artifacts affecting prefrontal channels. To tackle this, the authors introduce a novel deep learning model, MultiResUNet3p, which effectively removes these artifacts and reconstructs clean EEG signals. The research highlights the importance of combining EEG and ECG features, achieving 96.12% accuracy in binary classification (Positive vs. Negative emotions) and 94.25% accuracy in multiclass classification (Happy, Anger, Disgust, Fear, Neutral, and Sad).

**2. What are the emotions classified and how are they classified?**

The study classifies six emotions:  
Happy  
Anger  
Disgust  
Fear  
Neutral  
Sad

The classification is performed using machine learning models trained on features extracted from EEG and ECG signals. The dataset used in the study includes video stimuli designed to evoke specific emotions, and physiological responses are recorded during exposure. The classification is done using binary emotion classification (Positive vs. Negative) and multiclass classification (six emotions). The best performance was achieved by combining 112 features from EEG and ECG signals.

**3. How are the emotions extracted or identified from the obtained ECG signals?**

The ECG signals are processed to extract time-domain (TD), frequency-domain (FD), and time-frequency domain (TFD) features. These features capture variations in heart rate, signal morphology, and spectral characteristics, which correlate with emotional states. The extracted features are then fed into machine learning models, which classify emotions based on patterns observed in the ECG signals.

4. Talk in detail about the preprocessing of the ECG signals

ECG signals undergo several preprocessing steps to remove noise and artifacts:

* Notch Filtering: A 50 Hz notch filter is applied to remove power line interference.
* Bandpass Filtering: A Butterworth bandpass filter (0.05 Hz to 60 Hz) is used to eliminate unwanted frequencies.
* Resampling: The ECG signals are resampled to 256 Hz to match the sampling rate of other modalities.
* Segmentation: The signals are divided into 2-second intervals for feature extraction.
* Normalization: Z-score normalization is applied to ensure consistency across different signal segments.

**5. Talk in detail about features of the ECG signals used to train the model**

The study extracts 191 features from ECG signals, categorized into:

* Time-Domain Features (TD): Includes mean absolute value, waveform length, zero crossing rate, root mean square, and signal entropy.
* Frequency-Domain Features (FD): Includes spectral entropy, spectral centroid, spectral skewness, and spectral roll-off.
* Time-Frequency Domain Features (TFD): Extracted using Discrete Wavelet Transform (DWT), including band power, fractal length, and waveform length of wavelets.

These features help capture variations in heart rate and signal morphology, which are indicative of emotional states.

**6. Talk in detail about the ML model used and about the dataset and how they trained the model (very important)**

Machine Learning Model

The study evaluates multiple machine learning classifiers, including:

* Support Vector Machine (SVM)
* XGBoost Classifier (XGB)
* Extra Trees Classifier (ETC)
* Random Forest Classifier (RFC)
* MLP Classifier
* K-Nearest Neighbors (kNN) Classifier

The best performance was achieved using EEG and ECG features combined, with 5-fold cross-validation ensuring robust evaluation.

**Dataset**

The dataset used is ECSMP: A dataset on emotion, cognition, sleep, and multi-model physiological signals. It includes 87 participants, but only 52 participants had simultaneous recordings of EEG, ECG, and PPG signals. The participants were exposed to six emotional video clips, and their physiological responses were recorded.

**Training Process**

Feature Extraction: Features were extracted from EEG, ECG, and PPG signals.

* **Feature Selection:** Techniques like Decision Tree-Based Selection, PCA, ReliefF, and LASSO were used to select the most relevant features.
* **Model Training:** The dataset was split into 80% training and 20% testing, and 5-fold cross-validation was performed.
* **Emotion Classification: The** models were trained to classify binary emotions (Positive vs. Negative) and six emotions.

7. What are the results obtained and what is the actual outcome?

The study achieved high accuracy in emotion classification:

* Binary Classification (Positive vs. Negative emotions): 96.12% accuracy
* Multiclass Classification (six emotions): 94.25% accuracy

Best performance was achieved using EEG and ECG features combined. The results demonstrate that integrating multiple physiological signals significantly improves emotion recognition accuracy, making the system highly effective for real-world applications.

**8. What are the limitations found?**

Despite the high accuracy, the study has some limitations:

* Limited Dataset: Only 52 participants had simultaneous recordings, which may affect generalizability.
* EEG Artifacts: Prefrontal EEG channels were highly contaminated by eye blink artifacts, requiring advanced preprocessing.
* Feature Selection Complexity: The large number of extracted features increases computational complexity.
* Real-World Application Challenges: The system needs further validation in uncontrolled environments.

**9. Most Important: What is the research gap of this paper?**

The research gap identified in this paper includes:

* Limited Generalization: The study focuses on a specific dataset, and further validation is needed on diverse populations.
* Real-Time Implementation: The proposed method is not tested in real-time applications, which is crucial for practical use.
* Emotion Complexity: The study classifies six basic emotions, but complex emotional states (e.g., mixed emotions) are not explored.
* Multimodal Fusion Optimization: While EEG and ECG signals are combined, optimal fusion strategies for real-world applications need further investigation.
* Artifact Removal Improvements: The MultiResUNet3p model effectively removes eye blink artifacts, but other EEG artifacts (e.g., muscle noise) need better handling.

**Final Thoughts**

This paper provides a strong foundation for emotion recognition using multimodal physiological signals. If you're planning to extend this research for your project, you could focus on:

* Real-time emotion detection
* Expanding the dataset for better generalization
* Exploring deep learning models for improved feature extraction
* Investigating complex emotional states beyond basi**c classifications**



**Paper 6: DREAMER: A Database for Emotion Recognition through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices**

**Detailed Summary of the Paper**

The paper "DREAMER: A Database for Emotion Recognition through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices" presents a multimodal database containing electroencephalogram (EEG) and electrocardiogram (ECG) signals recorded from 23 participants during affect elicitation via audio-visual stimuli. Participants self-assessed their emotions in terms of valence, arousal, and dominance after each stimulus. The study aims to explore the potential of low-cost, wireless, portable devices for emotion recognition applications, comparing their performance with traditional medical-grade devices.

Key Questions Answered

**1. What is the paper talking about?**

The paper introduces DREAMER—a database designed for affect recognition using EEG and ECG signals recorded via portable, wireless, off-the-shelf devices. The objective is to evaluate the effectiveness of these low-cost devices in emotion recognition and establish a baseline performance using supervised classification models, specifically Support Vector Machines (SVMs).

**2. What are the emotions classified and how are they classified?**

* The emotions are classified based on the dimensional model of affect, specifically:
  + Valence (positive vs. negative feelings)
  + Arousal (excited vs. bored)
  + Dominance (sense of control vs. helplessness)
* The classification relies on self-assessment ratings by participants after exposure to film clips, using five-point scales for each dimension.

**3. How are the emotions extracted or identified from ECG signals?**

* Emotions are extracted by analyzing heart rate (HR) and heart rate variability (HRV) from ECG signals.
* The Pan-Tompkins QRS detection algorithm is used to locate the QRS complexes in the ECG signal.
* Changes in HR and HRV correlate with emotional states such as fear, sadness, happiness, and excitement.

**4. Detailed Preprocessing of ECG Signals**

* ECG signals have higher voltage amplitudes and low susceptibility to interference, minimizing the need for intensive preprocessing.
* However, artifact removal techniques are applied to ensure signal quality.
* The signals are then segmented to focus on the last 60 seconds of each film clip, where emotional responses stabilize.

**5. Features of ECG Signals Used to Train the Model**

* Heart Rate (HR): Changes in HR reflect emotional intensity.
* Heart Rate Variability (HRV): Measures variations in heart rate, correlating with different emotions.
* Time and Frequency Domain Features: Extracted from HR and HRV to quantify emotional responses.

**6. Machine Learning Model Used and Dataset Details**

* Model: Support Vector Machines (SVM) are used for classification.
* Dataset: 23 participants watched 18 film clips that elicited emotions.
* Training Process:
  + EEG and ECG signals were preprocessed and features extracted.
  + Features were fed into the SVM classifier, trained using participant-wise **classification to determine affective states.**

**7. Results Obtained and Actual Outcome**

* Classification results for valence, arousal, and dominance were comparable to results achieved using expensive, medical-grade equipment.
* This suggests that low-cost devices can be used for affect recognition applications in everyday scenarios.

**8. Limitations Found**

* Signal Quality: Low-cost devices may have lower signal resolution compared to medical-grade equipment.
* Participant Bias: Self-assessment ratings may introduce subjectivity.
* Limited Dataset: Only 23 participants, which might affect generalizability.

**9. Research Gap Identified**

* Limited Emotion Categories: The study focuses only on valence, arousal, and dominance, without exploring specific discrete emotions like anger, fear, or joy.
* Generalizability Issues: The model is trained participant-wise, raising concerns about whether the findings can be applied to broader populations.
* Device Performance Evaluation: More comparative studies are needed to fully validate the effectiveness of off-the-shelf EEG/ECG devices in real-world applications.