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Report On

"Emotion Recognition for Everyday Life Using Physiological Signals from Wearables "

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

*This is to certify that the seminar report entitled "**Emotion Recognition for Everyday Life Using Physiological Signals from Wearables**" is a bonafide work done by "THOGARUCHESTI HEMANTH (HTNO:205U1A05D2)" in the partial fulfillment of Bachelor of Technology in Computer Science and Engineering from JNTU, Hyderabad during the year 2020-24.*

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DECLARATION

I declare that the seminar report entitled "Emotion Recognition for Everyday Life Using Physiological Signals from Wearables "recorded in this report does not form part of any other thesis on which a degree has been awarded earlier. I, further declare that this seminar report is based on my work carried out at the "AVN Institute of Engineering and Technology" in the I Semester of our final year B.TECH course.

Date: **Signature**

Place: Hyderabad Thogaruchesti Hemanth

ABSTRACT

Smart wearables, equipped with sensors monitoring physiological parameters, are becoming an integral part of our life. In this work, we investigate the possibility of utilizing such wearables to recognize emotions in the wild. In most reviewed papers, the authors apply a similar procedure consisting of participant recruitment, stimuli preparation and annotation, signal collection and processing, self-assessment, and machine learning model learning and validation. Besides, we identified seven emotion recognition scenarios and analysed the transition from psychological models to machine learning tasks. Even though the majority of the research was performed in the laboratory environment, we conclude that studies in the field are feasible. They require especially:

(1) new self-assessment and triggering procedures adjusted to a real-life scenario.

(2) more attention to the machine learning process, including suitable deep learning architectures, revision of the data imbalance problem, and subject-specific data processing.

(3) adequate validation procedures.

(4) consideration of the model generalizability versus persuasibility.

(5) Comfortable devices able to provide reliable measurements in motion. Additionally, more large-scale studies are necessary to increase result credibility.We also postulate actions toward replicability and comparability of the research.

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1 INTRODUCTION

Emotion recognition through wearable technology has emerged as a groundbreaking approach to understanding and documenting human emotions in everyday life. In a world characterized by an increasing reliance on digital devices, the integration of psychological signals from wearables offers a unique opportunity to delve into the intricacies of our emotional experiences. This innovative method goes beyond traditional self-reporting, providing a more objective and nuanced perspective on emotions.

Wearables, ranging from smartwatches to biosensors, are equipped with the capability to capture a myriad of physiological and psychological signals. These signals, such as heart rate variability, skin conductance, and even facial expressions, serve as invaluable indicators of emotional states. By harnessing these signals, researchers and professionals can gain deeper insights into the easy and flow of emotions in real-world scenarios.

This approach to emotion recognition holds immense potential for documentation, shedding light on the emotional landscapes of individuals as they navigate the complexities of their daily lives. Whether in professional settings, social interactions, or personal moments, wearable technology allows for a seamless and continuous monitoring of emotional responses.

Moreover, the data obtained from these wearables can contribute to a more comprehensive understanding of mental health, stress levels, and overall well-being. The ability to document and analyze emotional patterns over time opens avenues for personalized interventions, facilitating the development of targeted strategies to improve emotional resilience and mental health.

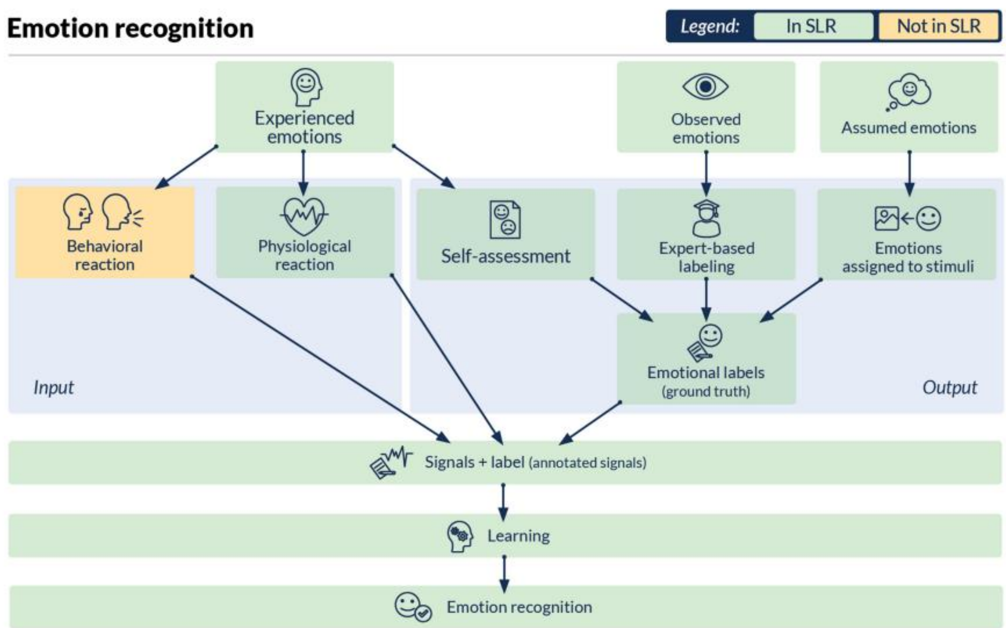

Figure-1.1 **Emotion Recognition Structure**

As we embark on this journey of emotion recognition through wearable technology, ethical considerations and privacy concerns come to the forefront. Striking a balance between the benefits of data-driven insights and the protection of individual privacy is paramount. However, with responsible development and implementation, the potential benefits for both research and individual well-being are vast.

TABLE 1.1

Usability of the most popular emotion Recognition Methods for field studies

Feature	Facial expression	Speech	Physiology
Device	camera	microphone	wearable
Multipurpose devices	+	+	−/+
Continuous monitoring in everyday life	−	−	+
Tracking during physical exercises	−	−	−/+
Monitoring devices invisible	−/+	+	−/+
Main drawback	well visible face required	voice emission required	sensors touching body

1.1 Motivation

The motivation to employ wearable technology for emotion recognition in daily life documentation stems from an ardent pursuit of understanding and enhancing human emotional experiences. By leveraging these devices to capture psychological signals, there's an opportunity to gain real-time, objective insights into our emotional states. This quest isn't just about data. It's about empowering individuals with a heightened self-awareness, personalized support systems, and improved mental health interventions. It's driven by a desire to decode the intricacies of human emotions in diverse contexts, ultimately fostering more empathetic communication and contributing to a society that values emotional well-being as a crucial aspect of human life.

1.2 Existing System

Wearable Devices: Devices like smartwatches, fitness trackers, and specialized biosensors have been equipped with sensors that monitor physiological signals. These sensors can measure heart rate variability, skin conductance, temperature, and even movement patterns to infer emotions.

Facial Expression Analysis: Some wearable cameras or head-mounted devices are designed to track facial expressions. They use algorithms to analyze changes in facial muscles, allowing for the recognition of emotions like happiness, sadness, anger, or surprise.

Speech and Voice Analysis: Wearables with microphones capture speech and voice data, employing algorithms to detect emotional cues in tone, pitch, and speech patterns. These can help recognize emotions like stress, excitement, or anxiety based on speech analysis.

Machine Learning Algorithms: Many of these systems rely on machine learning algorithms to process the data collected from wearables. These algorithms are trained on large datasets to recognize patterns associated with specific emotional states.

Real-Time Feedback: Some systems provide real-time feedback to users about their emotional states. For instance, a wearable device might alert someone when it detects heightened stress levels, prompting them to take steps to manage their emotions.

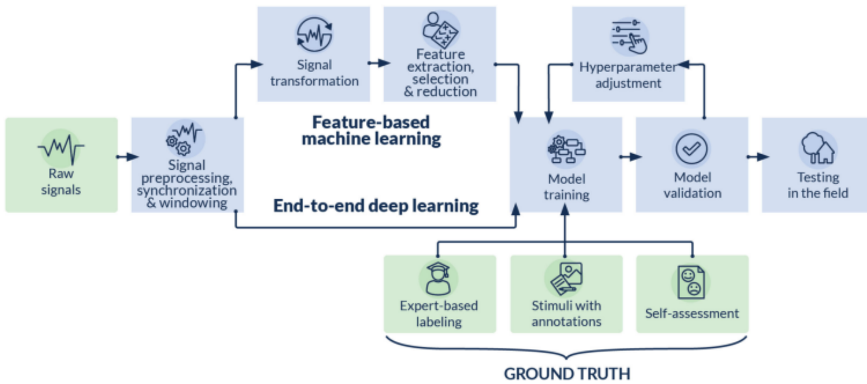

Figure-1.2 **Machine Learning Procedure for emotion recognition using biological signals from wearables.**

Applications in Mental Health: Emotion recognition systems in wearables have found applications in mental health monitoring. They can track changes in emotional states over time, offering insights into mood disorders, stress levels, and overall mental well-being.

Advancements in technology and ongoing research continue to drive the evolution of systems for emotion recognition using wearables. These systems hold the potential to provide valuable insights into human emotions and behavior in everyday contexts, contributing to a more emotionally aware and responsive society.

1.3 Proposed System

The proposed system delineates a comprehensive approach for emotion recognition through wearable devices, employing a multifaceted process. It commences with the collection of diverse physiological signals, leveraging wearable technology such as smartwatches and sensors to capture data across real-life scenarios. Signal processing techniques are then applied, encompassing preprocessing methods to refine raw data and subsequent feature extraction to identify pertinent markers indicative of emotional states. Machine learning algorithms are employed for emotion classification, training on labeled datasets to discern patterns between physiological signals and emotions. Rigorous validation and testing ascertain the system's accuracy and generalizability across demographics and scenarios. The envisioned integration of this system into existing wearables aims for user-friendly interfaces, potentially facilitating applications in mental health monitoring, human-computer interaction, and tailored user experiences. Ethical considerations surrounding data privacy and user consent are integral components addressed within this framework.

1.4 Problem Definition

Emotion recognition through wearables faces a series of intricate challenges. Accurately interpreting diverse physiological signals to differentiate nuanced emotional states requires robust algorithms capable of handling individual variability. Integrating data from multiple sensors poses a technical hurdle in forming a cohesive understanding of emotional states. Real-time processing for timely interventions, contextual understanding to discern emotions within different situations, and personalized recognition for individual experiences are critical yet challenging aspects. Ethical concerns around consent, data security, and privacy must be carefully addressed in the continuous collection of sensitive emotional data. Usability and user acceptance hinge on unobtrusive, user-friendly wearables. Combining expertise across psychology, data science, engineering, ethics, and design is pivotal for refining algorithms, enhancing sensors, ensuring privacy, and validating these systems for reliable and ethical deployment in everyday life.

2 LITERATURE SURVEY

Emotion and Decision Making" authored by J. S. Lerner, Y. Li, P. Valdesolo, and K. S. Kassam, published in the Annual Review of Psychology in 2015, delves into the intricate relationship between emotions and the decision-making process. This comprehensive review explores how emotions significantly influence and shape human decision-making across various contexts and scenarios

Thinking, Fast and Slow" is a seminal book written by Daniel Kahneman, a Nobel laureate in Economics, published in 2011. The book is a comprehensive exploration of the human mind and its decision-making processes, encapsulating decades of research in psychology and behavioural economics.

Emotion and Adaptation" authored by C. A. Smith and R. S. Lazarus is featured in the "Handbook of Personality: Theory and Research," published in 1990. This chapter provides a comprehensive exploration of the intricate relationship between emotions and the process of adaptation within the broader context of personality theory.

Wearable-based Affect Recognition—A Review," authored by P. Schmidt, A. Reiss, R. Durichen, and K. V. Laerhoven, was published in the journal Sensors in 2019. This review article provides an extensive overview and analysis of the state-of-the-art technologies and methodologies used in recognizing human affective states through wearable devices.

Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection," authored by P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. V. Laerhoven, was presented at the International Conference on Multimodal Interaction in 2018. This paper introduces the WESAD dataset, designed explicitly for research in wearable-based stress and affect detection.

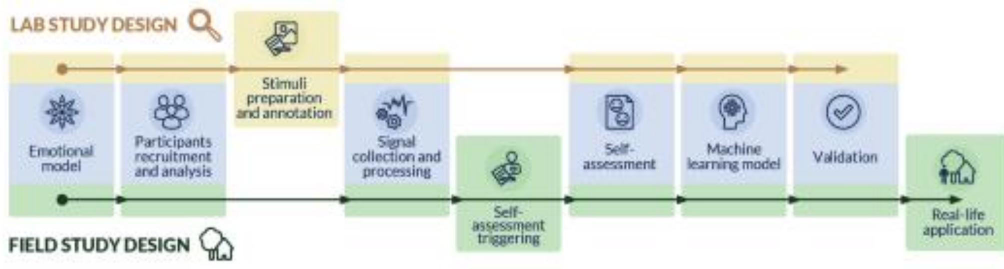

Figure-2.1 **Research stages for emotion recognition in the lab and in the field**

Table-2.1

The main Difference in emotion Recognition Between Lab study and field study

Category	Lab study	Field study
Emotions experienced	− In controlled environment − Impacted by unnatural conditions − Limited to the prepared stimuli + Beginning and end determined by the stimuli	+ In natural context + Full range of emotions − Occurrence is difficult to capture − Hard to determine the beginning and end
Stimuli	± Planned and prepared, e.g., videos, images, music, tasks + Fully controlled by researchers, may be interrupted + May be annotated + Known duration + No distractions nor unexpected stimuli + Condensed sequence of stimulants separated by wash out	+ Daily life stimuli − Unknown stimuli − No stimuli label − No starting point − Unknown duration − Out of researcher's control − Susceptible to life conditions, e.g., drugs, fatigue
Labeling (ground truth)	+ Self-assessment + Expert-annotated stimuli + Observed and derived by external experts	− Mainly self-assessment + Nearby person (relative, friend)
Self-assessment	+ Detailed + Often + Trigger time easy to determine + Triggered and filled out right after each stimuli	− Limited scope − Sporadic − Triggering time is difficult to determine ± Self-, event-, activity-, randomly-triggered, schedule, reasoning − Usually delayed participant's response [26]
Measuring physiology / devices	+ Medical-level, precise devices + Devices can be large and wired + Many devices simultaneously possible + External devices possible, e.g., multiple cameras + No battery problem − Stressful condition + High-quality signal / data (little external interference) + Stationary position (usually sitting)	− Lower quality of sensors and signals [37] + Personal, convenient, useful wearables − Only few devices feasible ± Battery-efficient wearables + Convenient and unnoticeable measuring − Artifacts caused by the movement and field conditions ± Data transfer to server (in real-time / post-session) − Lack of data when wearable is off / not worn − 24/7 technical support required
Additional factors	+ Static environment (temperature, lighting, etc.) + Meta-questions (e.g., health issues, time past since last coffee/activity/sleep) ± Relatively small amount of data	− Variable environment − No meta-question ± Large amount of data to be collected and processed

'+' Denotes an advantage; '−' is a disadvantage; '±' means an aspect has both, positive and negative sides.

3 METHODOLOGY

Signal Acquisition and Selection: Identify the psychological signals most relevant to emotion recognition. These could include heart rate variability, skin conductance, body temperature, facial expressions through cameras, voice tone analysis, or movement patterns captured by accelerometers.

Wearable Sensor Selection and Placement: Choose appropriate wearable devices capable of capturing the selected signals comfortably and unobtrusively. Determine optimal sensor placements to ensure accurate signal acquisition without hindering daily activities.

Data Collection in Ecologically Valid Settings: Conduct data collection in real-world environments where individuals experience a range of emotions naturally. Capture a diverse set of scenarios to ensure a comprehensive dataset reflective of everyday life.

Ground Truth Annotation: Annotate the collected data with ground truth labels indicating the emotional states experienced by individuals during data capture. This annotation can be based on self-reports, environmental context, or external observations, ensuring accuracy in training emotion recognition models.

Feature Extraction and Signal Processing: Process the raw sensor data to extract relevant features indicative of emotional states. This step involves techniques such as time-series analysis, frequency domain analysis, or machine learning-based feature extraction methods.

Emotion Classification and Modeling: Develop machine learning or AI models capable of recognizing and classifying emotions based on extracted features. Train these models using labeled datasets to accurately predict emotional states from wearable-derived signals.

Validation and Evaluation: Validate the developed models using separate datasets or cross-validation techniques to assess their accuracy, sensitivity, specificity, and generalizability. Evaluate the performance of the models across different individuals and diverse real-life scenarios.

Ethical Considerations and Privacy: Ensure compliance with ethical guidelines regarding data collection, storage, and usage. Safeguard individual privacy by anonymizing data and obtaining informed consent from participants.

Iterative Refinement and Improvement: Continuously refine the methodology based on feedback, addressing limitations, improving accuracy, and incorporating advancements in sensor technology or machine learning algorithms.

Real-Life Deployment and User Experience: Consider the practicality of deploying wearable devices for emotion recognition in everyday life. Evaluate user acceptance, comfort, and usability to ensure seamless integration into daily routines.

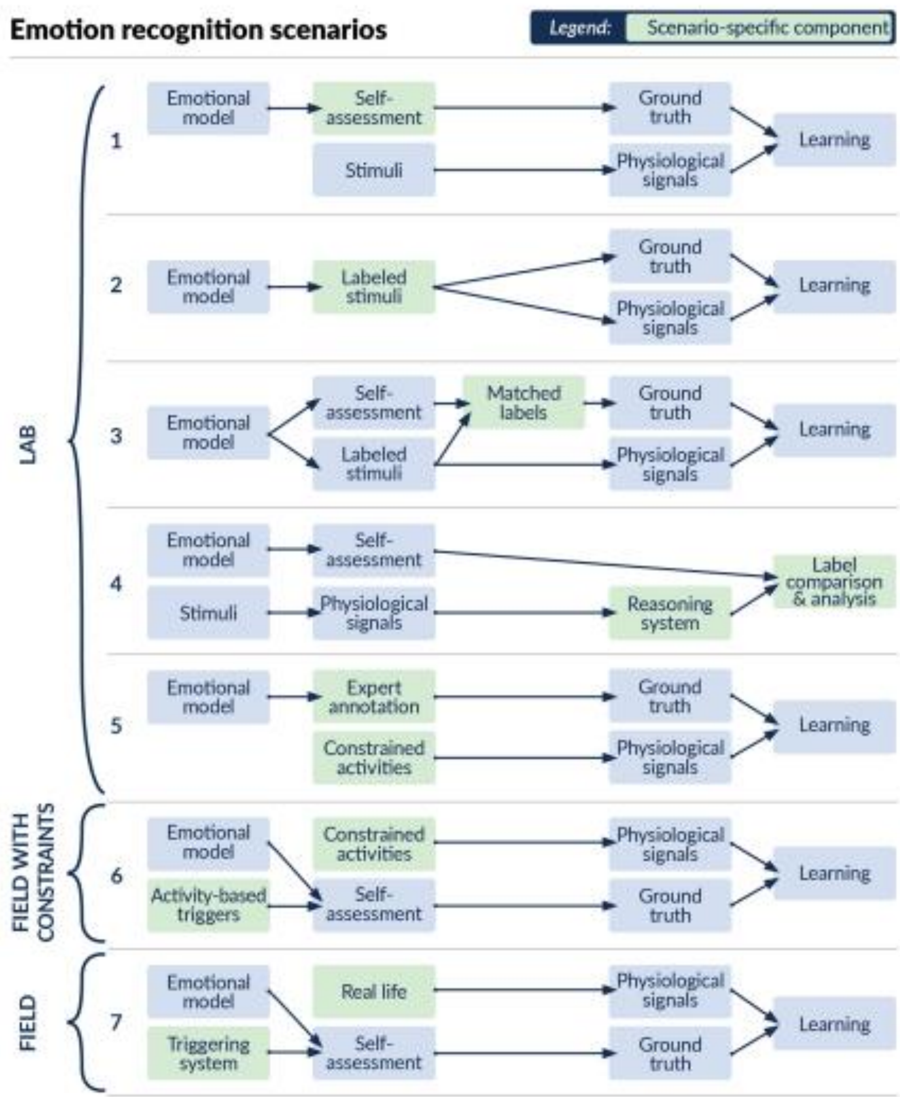

Figure-3.1 **Emotion Recognition Scenarios identified in Literature Survey**

4 PRE-PROCESSING

Preprocessing steps play a pivotal role in ensuring the accuracy and reliability of emotion recognition from physiological signals collected through wearables. The data collection phase encompasses the identification of wearable types, such as heart rate monitors or skin conductance sensors, along with specifying the sampling rates for each sensor. This documentation ensures clarity in understanding the sources of physiological data and the frequency at which they're sampled, crucial for replicating experiments.

Data cleaning procedures are integral to refining raw physiological signals. Techniques involving noise removal, whether through filtering methodologies to eliminate artifacts or interference, are outlined. Additionally, the handling of missing or unreliable data points, be it through interpolation, removal, or imputation, is detailed. These steps provide transparency in addressing data quality issues that could impact subsequent analyses.

The subsequent stage involves feature extraction from the refined physiological signals. The documentation delineates the extraction of time-domain features, such as statistical measures (mean, variance), offering insights into signal characteristics. Additionally, transformations to the frequency domain (e.g., Fast Fourier Transform) and extraction of frequency-domain features are recorded, elucidating the spectral components of the signals. If applicable, any extraction of nonlinear features, like entropy or fractal dimension, is elucidated to capture complex signal behaviours.

Normalization and scaling techniques applied to the extracted features are documented in this phase. This includes explanations of normalization procedures like Min-Max scaling or z-score normalization, providing an understanding of how feature values are standardized, ensuring a level playing field for subsequent analyses and model training.

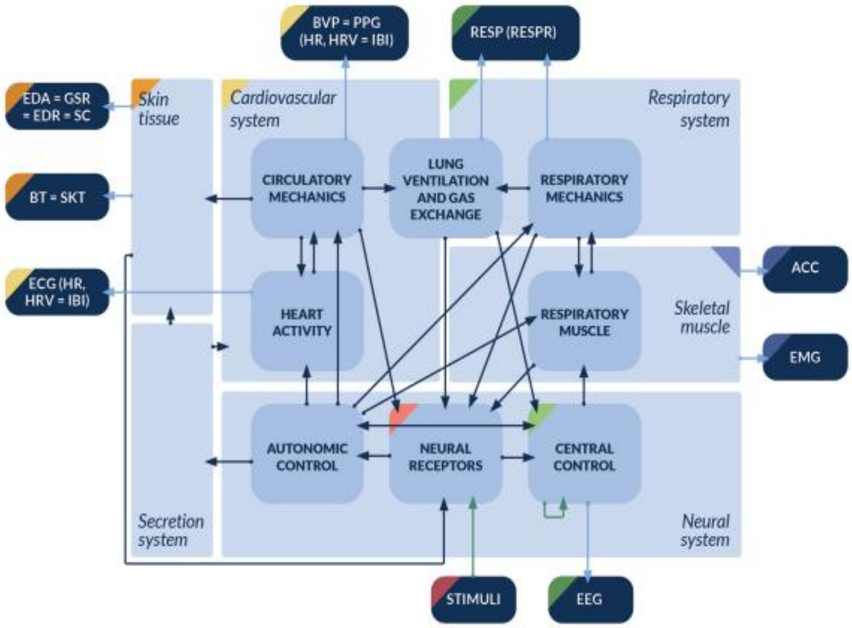

Figure -4.1 **Interrelationships between physiological systems and bio signals.**

Finally, the feature selection or reduction strategies employed to refine the dataset are detailed. Documentation of dimensionality reduction techniques, such as Principal Component Analysis (PCA) or feature selection based on importance, offers insights into how the most relevant and discriminative features are chosen, streamlining the dataset for subsequent emotion recognition model development.

5 RESULT & ANALYSIS

The utilization of diverse validation methods in the domain of emotion recognition through physiological signals from wearables has yielded multifaceted results, offering insights into the robustness and generalizability of models across different scenarios and individuals. Intra-subject validation methods, encompassing one-time splits, k-fold cross-validation, and leave-one-case-out techniques, highlighted the importance of understanding individual variations in emotional responses. These methods allowed for the assessment of model performance within subjects, emphasizing the need for personalized recognition approaches due to the intricate nature of emotions and physiological responses.

In contrast, inter-subject validation methods, such as one-time splits and leave-one-subject-out validation (LOSO), delved into the model's ability to extrapolate emotion recognition capabilities to unknown individuals. The application of LOSO, particularly prevalent across multiple mature studies, underscored the significance of assessing models on entirely new subjects. This approach revealed insights into the model's performance in recognizing emotions for individuals not included in the training set, reflecting a more realistic and practical evaluation of the model's capabilities in real-world scenarios.

Moreover, the hybrid approach of inter-intra-subject validation, combining generalized models with personalized ones using methods like LOSO alongside repeated random splits on remaining subject data, showcased the potential of blending personalized and generalized recognition strategies. This method aimed to strike a balance between individualized responses and generalizable models, hinting at the prospect of creating adaptive recognition systems capable of accommodating both individual variations and broader emotional patterns.

Additionally, task-based cross-validation and across-time validation methods provided nuanced evaluations of model performance in varied contexts. Task-based assessments scrutinized the model's adaptability across different activities within the same subjects, shedding light on its versatility in recognizing emotions within diverse behavioral settings. Across-time validation, on the other hand, examined the model's consistency and adaptability over time, demonstrating its capability to recognize emotions in later periods based on earlier learned data.

The array of validation methods employed in these studies underscored the complexity of emotion recognition from physiological signals. While intra-subject validations emphasized personalized recognition, inter-subject and hybrid validations showcased the necessity of models capable of reasoning for new and unknown subjects. Task-based and across-time validations further accentuated the adaptability and temporal consistency of these models, collectively contributing to a deeper understanding of their performance across diverse scenarios and timeframes.

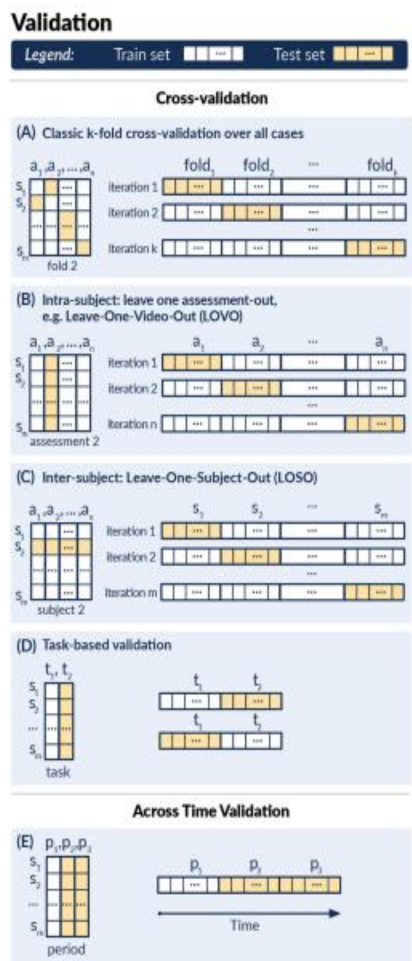

Figure -5.1

<u>Selected validation methods used in emotion recognition</u>

6 CONCLUSION

Our primary aim was to explore the potential of wearables in recognizing emotions within everyday contexts. From this extensive search, we aiming to decipher whether wearables indeed hold promise for this purpose. While our findings suggest the feasibility of employing wearables for emotion recognition in daily life, our investigation underscores the necessity for further in-depth exploration. Notably, we identified a transition from controlled laboratory setups to field environments in recent studies. However, this shift necessitates the development of comfortable, motion-compatible devices capable of delivering reliable measurements, coupled with user-friendly self-assessment triggering mechanisms.

Within our review, several positive observations emerged. Firstly, it became evident that recognizing emotions using physiological signals from wearables is indeed viable. Moreover, the availability of numerous off-the-shelf wearable devices equipped for field investigations is encouraging. Furthermore, the utilization of deep learning architectures has surfaced as a promising avenue, offering novel solutions for addressing the complexities encountered in field studies.

Despite these optimistic findings, our review also highlighted several areas of concern and limitations within the existing literature. Primarily, the majority of studies remained confined to laboratory settings, limiting the generalizability of findings to real-life scenarios. Additionally, a common trend involved simplifying the classification of emotions into binary or few-class problems, potentially oversimplifying the nuanced nature of human emotions. Neglect of crucial stages within the machine learning process, particularly addressing imbalanced learning samples, was also notable. Moreover, the reproducibility of research in this domain appears challenging, raising concerns about the reliability and replicability of findings—a critical aspect for scientific advancement.

7 FUTURE WORK

Looking into the future, the scope of emotion recognition using physiological signals from wearables holds tremendous potential for transformative advancements. One of the most promising trajectories involves the refinement of wearable sensor technology. Enhancements in sensor capabilities, such as improved accuracy, sensitivity, and miniaturization, will enable more precise and unobtrusive data collection in diverse real-life scenarios. This evolution will likely involve the integration of multi-modal sensors, combining physiological data with contextual information, like environmental factors or social cues, to create a richer understanding of emotional states. Additionally, the development of wearable devices that seamlessly blend into everyday clothing or accessories could further encourage continuous, naturalistic data capture, paving the way for more robust and comprehensive emotion recognition systems.

Furthermore, the future of emotion recognition using wearables is likely to witness substantial advancements in machine learning and data analytics techniques. Deep learning architectures have shown promise in handling complex patterns within physiological data. Future research might explore more sophisticated models capable of capturing subtle emotional nuances, addressing imbalanced datasets, and adapting to individual variations in emotional expression. Additionally, the integration of explainable AI techniques could provide insights into how these systems arrive at emotion classifications, enhancing transparency and trust in their decisions.

Ethical considerations and user-centric design will continue to play pivotal roles in shaping the future landscape of wearable-based emotion recognition. Striking a balance between data privacy, informed consent, and technological innovation will be imperative. User acceptance and adherence to wearables for emotion recognition hinge on designing devices that prioritize comfort, aesthetics, and seamless integration into daily life while maintaining robust data security measures. Collaborative efforts across interdisciplinary domains, including psychology, ethics, engineering, and user experience design, will be crucial in steering the evolution of these systems toward ethical, reliable, and user-friendly solutions that empower individuals in managing their emotional well-being.

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9 Appendix

Emotion recognition through physiological signals obtained from wearables has emerged as a promising avenue for understanding and enhancing everyday life experiences. This innovative approach leverages advancements in wearable technology to capture and analyse physiological data, providing insights into an individual's emotional state. In this context, the use of wearables, such as smartwatches and fitness trackers, has become integral to monitoring physiological signals like heart rate, skin conductance, and body temperature

The appendix of this discussion outlines the key methodologies and technologies employed in emotion recognition through wearable devices. One of the primary physiological signals utilized is heart rate variability (HRV). HRV reflects the variation in time intervals between successive heartbeats, offering a window into the autonomic nervous system's activity. High HRV is associated with a more adaptable and resilient nervous system, while low HRV may indicate stress or emotional arousal. Wearables equipped with photoplethysmography sensors enable real-time monitoring of HRV, providing valuable data for emotion recognition algorithms.

Skin conductance is another crucial physiological signal harnessed for emotion detection. This metric measures the electrical conductance of the skin, which varies with sweat gland activity influenced by emotional responses. Wearables with integrated electrodermal sensors can capture changes in skin conductance, offering a direct reflection of emotional arousal levels. This information is particularly useful in discerning moments of stress, excitement, or relaxation in everyday life.

The appendix further details the integration of machine learning algorithms in processing physiological data for emotion recognition. Supervised learning models, trained on labeled datasets correlating physiological signals with known emotional states, enable wearables to predict emotions in real-time. These algorithms adapt and refine their predictions over time, enhancing their accuracy and reliability. The development of user-specific models, considering individual variations in physiological responses, contributes to the personalization of emotion recognition systems.

The appendix also addresses the challenges associated with emotion recognition through wearables. Factors such as data privacy, user comfort, and the need for continuous signal accuracy are critical considerations. Wearable devices must strike a balance between unobtrusiveness and functionality to ensure widespread adoption and sustained usage in everyday life

Moreover, the ethical implications of emotion recognition technology are discussed in the context of potential misuse and the importance of informed consent. The inclusion of guidelines and safeguards within wearable devices, as outlined in the appendix, is imperative to protect user privacy and prevent unauthorized access to sensitive emotional data.

In conclusion, the appendix provides a comprehensive overview of the methodologies, technologies, and challenges associated with emotion recognition using physiological signals from wearables. This innovative approach holds immense potential to enhance our understanding of emotions in everyday life, paving the way for personalized well-being interventions and improved human-computer interactions. As technology continues to advance, the integration of emotion recognition into wearables is poised to play a transformative role in shaping the future of human-machine interfaces and emotional well-being.