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Emotion Recognition

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This work was completed in the Department of Electrical Engineering at the University of Blida.
We thank God for granting us the strength and will to begin and complete this thesis.
First, this work would not have been this rich and possible without the assistance and guidance of Dr. I. Kaoula. We thank her for her outstanding supervision, patience, precision, and availability during our preparation of this thesis.
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Finally, we also thank our dear parents, who supported us throughout our journey. We reiterate our gratitude to everyone who helped us, directly or indirectly, in completing this project, not to mention the teachers who contributed to our training.

Dedication

It is with great pleasure that we dedicate this work

To our dear father

Who never stopped advising, encouraging, and supporting us throughout our studies and who was behind us, guiding us in the right direction so that we could achieve our goals.

To our dear mother

Who supported, encouraged, and gave us love and vitality throughout our lives. We wish you sincerely for your affection, your kindness, your guidance, and your presence at our side, which has always been our source of strength to face various obstacles.

May God keep our parents and wish them more happiness and joy in their lives.

To my brother and sisters, To all members of my family, young and old.

To my friend Nahla , who was the reason for our returns,

To our supervisor Dr. I. KAOULA

Who shared with us all the emotional moments while completing this work

To who have always encouraged and wish us more success,

ملخص:

يقدّم هذا المشروع نظامًا شاملاً للتعرف على المشاعر في الوقت الحقيقي، وفقًا للاستجابات السلوكية والفسيولوجية. يعتمد النهج المقترح على الرؤية الحاسوبية لاستخراج الحالات العاطفية وتفسيرها من تدفقات الفيديو المباشر. يُستخدم DeepFace للكشف عن ملامح الوجه وتحليلها لتصنيف المشاعر البصرية، بينما يُستخدم التصوير الضوئي عن بعد (rPPG) لتقديرإشارات معدل ضربات القلب باستخدام طريقة تعتمد على اللون (CHROM). من خلال الجمع بين هاتين الطريقتين، يعزز النظام دقة اكتشاف المشاعر، خاصة في البيئات الواقعية والديناميكية. يتضمن البحث تطوير خوارزمية مفصلة وتنفيذ النظام مع تقييم مجموعة البيانات والاختبار في الوقت الفعلي، مما يدل على قدرة النظام على إجراء مراقبة مستمرة غير تلامسية للمشاعر. يُعد هذا الإطار متعدد الوسائط واعدًا بشكل خاص في مجال الرعاية الصحية والتفاعل بين الإنسان والحاسوب وتطبيقات الحوسبة العاطفية.

الكلمات المفتاحية

الوقت الحقيقي، الرؤية الحاسوبية ، الحالات العاطفية، الفيديو المباشر، DeepFace ، التصوير الضوئي عن بعد (rPPG)، الطريقة القائمة على اللون (CHROM).

Résumé :

Ce projet présente un système complet de reconnaissance des émotions en temps réel basé sur les réponses comportementales et physiologiques. L'approche proposée s'appuie sur la vision par ordinateur pour extraire et interpréter les états émotionnels à partir de flux vidéo en direct. DeepFace est utilisé pour détecter et analyser les traits du visage afin de classer visuellement les émotions, tandis que la photopléthysmographie à distance (rPPG) est utilisée pour estimer les signaux de fréquence cardiaque grâce à une méthode basée sur la couleur (CHROM). En combinant ces deux méthodes, le système améliore la précision de la détection des émotions, notamment dans des environnements réalistes et dynamiques. La recherche comprend le développement détaillé d'algorithmes et la mise en œuvre du système, ainsi que l'évaluation d'ensembles de données et des tests en temps réel, démontrant la capacité du système à effectuer une surveillance continue et sans contact des émotions. Ce cadre multimodal est particulièrement prometteur pour les applications de santé, d'interaction homme-machine et d'informatique affective.

Mots-clés:

Temps réel, vision par ordinateur, états émotionnels, vidéo en direct, DeepFace, photogrammétrie à distance (rPPG), méthode basée sur la couleur (CHROM).

Abstract :

This project presents a comprehensive system for real-time emotion recognition based on behavioral and physiological responses. The proposed approach relies on computer vision to extract and interpret emotional states from live video streams. DeepFace is used to detect and analyze facial features for visual emotion classification, while remote photoplethysmography (rPPG) is used to estimate heart rate signals using a color-based method (CHROM). By combining these two methods, the system enhances the accuracy of emotion detection, especially in realistic and dynamic environments. The research includes detailed algorithm development and system implementation, along with dataset evaluation and real-time testing, demonstrating the system's ability to perform continuous, contactless emotion monitoring.

This multimodal framework is particularly promising in healthcare, human-computer interaction, and affective computing applications.
Keywords:
Real-time, computer vision, emotional states, live video, DeepFace, remote photogrammetry (rPPG), color-based method (CHROM).

List of acronyms

BPM: Beats Per Minute
CHROM: Chrominance method
Eqt: Equation
FER : Facial Emotion Recognition
FPS: Frame Per Second
FR: Face Recognition
HCI : Human Computer Interaction
HR : Heart Rate
Hz: Hertz
IBIs: Inter Beat Interval
PPG: Photoplethysmography
RGB: Red, Green, Bleu
ROI: Region Of Interest
rPPG: Remote Photoplethysmography

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General Introduction

Affective AI, also known as visual affective computing, is a branch that enables computers to analyze and understand human verbal, nonverbal cues, to assess their emotional state in real time analyzes in images and videos using computer vision technology to analyze an individual's emotional state.

This revolutionary technology aims to make human-machine interactions more natural and authentic. It is based on the theory of universal emotions, which states that despite the diversity of human nature and affiliations, humans exhibit six basic emotional states: happiness, fear, anger, surprise, disgust, and sadness. Emotions are not substances that can be transferred from one person to another, not simply organic questions whose secret lies within the body. Rather, they are relationships that cannot be described. What happens when we express our emotions? To the outside world, it's obvious that our facial expressions change, from the muscles at the corners of our lips to the movement of our cheeks, but there's much more to it. Our pupils may dilate, our heart rate temporarily slow or accelerate active.

How does this relate to our various emotions? When learning about emotions and trying to understand and decode them, this information is priceless, but without specialized methods, much of it remains incomprehensible. This is where emotion recognition technology comes in. Which is a set of hardware and software designed to detect expressed human emotions in all their complexity and convert them into data that can then be analyzed and even processed by computers. It may sound like impossible science fiction, but it's already a tangible reality. Emotion detection has become a pivotal area of research in recent years due to its transformative potential in fields such as human-computer interaction (HCI), mental healthcare, affective computing, and intelligent systems. The ability to accurately recognize human emotions in real time can enhance interactive systems by making them more adaptive, empathetic, and responsive to users' emotional states.

Traditional emotion recognition approaches typically rely on a single modality such as facial expressions, vocal tone, or physiological signals. However, each of these modalities suffers from specific limitations; facial recognition can be disrupted by motion or poor lighting .Physiological sensors, although informative, often require direct skin contact limiting their use in naturalistic settings.

Recent advancements in computer vision and deep learning have paved the way for more robust and flexible solutions. For instance, DeepFace a deep neural network has demonstrated near-human accuracy in classifying facial expressions. In parallel, remote photoplethysmography (rPPG) has emerged as a promising non-contact method for physiological monitoring. The CHROM algorithm analyzes subtle variations in skin color captured through video to estimate heart rate, which has been shown to correlate with emotional states through heart rate (HR). This makes rPPG particularly valuable for integrating physiological context into emotion detection frameworks.

This thesis explores the integration of behavioral and physiological responses to develop a multimodal emotion recognition system in real-time .It is structured as follows; The first chapter, it begins by lying a foundational understanding of emotions, detailing their definitions and importance, historical background, including the six major theories of emotion and their classification through basic and dimensional models. Chapter two, it includes a main perspective of emotion recognition techniques in the current decade, visual and Heart rate estimation. Discuss the limitations of Unimodal emotion detection systems, reinforcing the advantages of multimodal approaches for higher accuracy and reliability. The final chapter details the proposed system's architecture, methodology, and implementation. It covers the block diagram, and the fusion of facial and physiological data in real time. The thesis also documents the GUI design, algorithmic structure, and performance evaluation; conclude with a critical and constructive analysis of the resulting multimodal systems, discussing the system's effectiveness and future prospects.

Chapitre 1 **Understanding Emotion**

1.1 Introduction

Emotions are a fundamental part of the human experience. They shape our perceptions, influence our actions, and play a crucial role in our overall well-being. Understanding and harnessing the power of emotions can lead to profound personal growth and self-realization. Therefore, it's not surprising that researchers have developed numerous theories about how emotions are generated and how they influence our thinking. This question is directly related to fundamental aspects: What is emotion, how many emotions can be identified, and how can they be represented and modeled? These questions have stimulated numerous studies, and the representation and modeling of emotions remains a topic of debate. Below, we discuss several key concepts of emotions that have become central to human behavioral research.

1.1.1 What Are Emotions

Emotions are physical and mental states brought on by neurophysiological changes, variously associated with thoughts, feelings, behavior responses, and a degree of pleasure or displeasure. Emotion is "A strong feeling deriving from one's circumstances, mood, or relationships with others"'[1-5]. We all have them. They come and go every day of our lives, but how much do we really know about their purpose?

Figure1. 1 What are Emotions [W1]

In psychology, Pieron defines emotion as an emotional reaction of moderate intensity which depends on the diencephalons centers and generally manifests itself as vegetative symptoms. There is a conscience of emotion , although its intensity seems to vary[6].

In philosophy, emotion can generally be defined as an expression of emotional life which is generally accompanied y a pleasant or unpleasant state of consciousness. Emotion is a short-term disturbance and a break in imbalance. Emotions are at the heart of our lives, and we attach great importance to them. The philosophical problems raised by the existence of emotions, which many great philosophers of the past have struggled with, revolve around attempts to understand the meaning of these emotions[7]. Are emotions feelings, thoughts, or experience ?.

According to the American Psychological Association (APA), emotion is defined as “a complex reaction pattern, involving experiential, behavioral and physiological elements”. They are how individuals react to things or situations they find personally significan[8].

Figure1. 2 The Intersection of Philosophy and Psychology [W2]

1.1.2 Historical of Emotion

Thinkers and philosophers have long been interested in human nature and its accompanying bodily sensations. More broadly, this has also been of great interest to Western and Eastern societies alike. Emotional states have been associated with divine presence and with the enlightenment of the human mind and body. The ever-changing actions and moods of individuals have been of great interest to most Western philosophers, including Aristotle, Plato, Descartes, Aquinas, and Hobbes, leading them to propose extensive—and often competing—theories that sought to explain emotion and the motives that accompany human action, as well as its consequences[9].

The word “emotion”, has named a psychological category and a subject for systematic enquiry only since the 19th century[10]. Before then, relevant mental states were categorized variously as “appetites,” “passions,” “affections,” or “sentiments.” The word “emotion” has existed in English since the 17th century, originating as a translation of the French emotion, meaning a physical disturbance. It came into much wider use in 18th-century English[11].

Emotions have appeared in history, and related writings, for centuries. History writing has sometimes focused on the emotional side; in eighteenth-century Europe, the centrality of the idea of sympathetic exchange in communication ensured that many historians of the period sought to evoke emotions in their readers. The emotions of historical subjects have long been of interest. For some early twentieth-century theorists, who often relied on eighteenth-century histories of human development, human emotions became more sophisticated over time, demonstrating the "civilization" of different nations[12].

As we move through our daily lives, we experience a variety of emotions. Emotion is a subjective state of being that we often describe as our feelings. Emotions result from a combination of subjective experience, expression, cognitive appraisal, and physiological responses. Historians, like other sociologists, assume that emotions, feelings, and their expressions are regulated in different ways across cultures and historical periods.More recently, researchers have sought to explore emotion as a powerful analytical lens, a dimension of cognition and decision-making, and something to be embraced rather than avoided. Thus, the history of emotions, as it has emerged in the past twenty years, has many precedents[13].

The historical trajectory of emotion theory reflects an ongoing interaction between philosophy, psychology, and neuroscience. From early discussions of the rationality of emotion to recent studies of its biological foundations, these fundamental perspectives continue to shape research in affective science, artificial intelligence, and human-computer interaction[14].

Figure1. 3 Researching the Historical of Emotions [W3]

1.1.3 The Sixth Theories of Emotions

Emotion is multifaceted and debatable. Defining it remains an unfinished task. Many researchers continue to propose theories about the elements that constitute our emotions, each building on the others [W4]. These existing theories face ongoing challenges. Among them are the following.

- **The Evolutionary Theory of Emotion**

  According to the evolutionary theory of emotion, proposed by naturalist Charles Darwin, our emotions exist because they serve an adaptive role. Emotions motivate people to respond quickly to stimuli in the environment, which helps improve their chances of success and survival.

- **The James-Lange Theory of Emotion**

According to the James-Lange theory of emotion, an external stimulus triggers a physiological reaction. Your emotional reaction depends on how you interpret those bodily responses. According to this theory, you don't tremble because you're afraid; you feel afraid because you tremble.

- **The Cannon-Bard Theory of Emotion**

According to the Cannon-Bard theory of emotion, we feel emotions and experience physiological reactions such as sweating, trembling, and muscle tension simultaneously. We say that the physical and psychological experience of emotion occurs simultaneously, not sequentially.

- **Schachter-Singer Theory**

This theory, developed by Stanley Schachter and Jerome E. Singer, introduces the element of reasoning into the emotional process. The theory posits that when we experience an event that causes physiological arousal, we attempt to find the cause of this arousal. Consequently, we experience emotion.

- **Cognitive Appraisal Theory**

Richard Lazarus pioneered this theory of emotion. According to cognitive appraisal theory, reasoning must occur before emotion is experienced. Thus, a person first experiences a stimulus, then reflects, and then simultaneously experiences a physiological response and an emotion.

❖ **Facial Feedback Theory of Emotion**

Facial feedback theory suggests that emotions are directly related to changes in facial muscles. For example, people who are forced to smile pleasantly at a social event will enjoy the event more than if they frown or wear a more neutral facial expression.

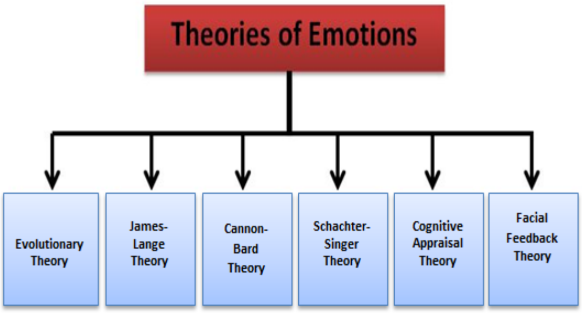

Figure1. 4 The Six Theories of Emotions

1.2 Type of Emotion

Emotions are common, dynamic sequences that occur throughout our days and set the tone for our lives[15]. According to emotion research, there are believed to be two distinct types of emotions that humans feel

1.2.1 Primary Emotions

Primary Emotions are our immediate emotional response to what just happened. These emotions typically make sense and are straightforward. When a good friend moves away, you feel sadness. If someone tells you how much you've helped them, you feel happy. In fact, these primary emotions are the raw material from which all other emotions can be made[16].

1.2.2 Secondary Emotions

Secondary Emotions are emotional reactions to primary emotions. They are emotions about our emotions, and are often more intense. Imagine you're feeling anxious about having to do a class presentation this semester in an English class. The nervousness is primary, but suddenly this shifts. Then, you start to feel frustrated, disappointed, and embarrassed for feeling anxious about public speaking[16].

Primary Emotion	Secondary Emotion
Joy	*Hopeful, proud, excited, delighted*
Fear	*Anxious, insecure, inferior, manic*
Anger	*Resentment, hate, envy, jealous, annoyed*
Sadness	*Shame, neglectful, depression, guilty, isolated*
Surprise	*Shocked, dismayed, confused, perplexed*

Table1. 1 Primary vs Secondary [W5]

1.3 Classification of Emotion

Emotion play a vital role in shaping human behavior and cognition. This section reviews the models used to classify emotions, focusing on their origins, functions, and relevance in interpersonal dynamics[17].

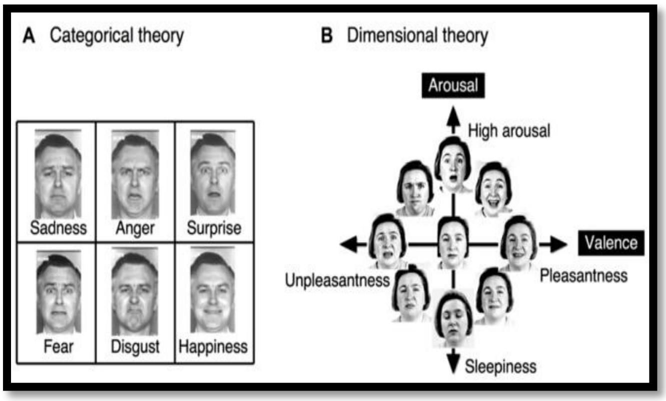

Figure1. 5 The two different theories regarding facial emotion perception [W6]

1.3.1 Categorical Emotion

It define emotions as discrete categories, this type assumes the existence of a set of basic emotions innate in humans, the expression and recognition of which are generally undifferentiated between individuals of different races or cultures. There are two types:

- **Basic Emotions:** They are universal across all human cultures and are believed to be biologically programmed. Paul Ekman , in 1992, identified six universal emotion : Happiness, Sadness, Fear, Anger, Surprise, and Disgust[18] .

- **Complex Emotions:** Unlike basic emotions, complex emotions arise from social and cognitive processes . Examples include Love , Guilt , Shame , Pride[19].

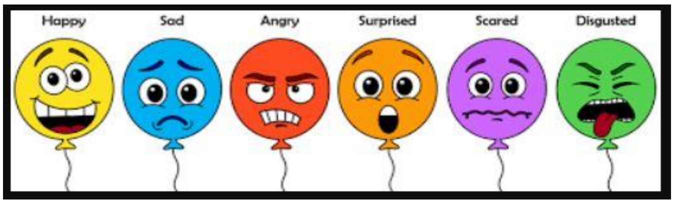

Figure1. 6 Basic Emotions [W7]

1.3.2 Dimensional Emotions:

The continuity of changes in emotional states might not be well captured by discrete models. To address the above issues, researchers have turned to the dimensional models which describe emotions as points in a space of different dimensions[20]. It based on Valence (positive/negative) and Arousal (high/low activation. These emotions are influenced by culture learning and context and often involve a combination of basic emotions. For example , Jealousy may be a combination of Anger, Sadness, and Fear.

- Russell's Circular Model of Affect (1980): Emotions are arranged in a circular structure, with Valence (unpleasant) representing on axis and Arousal (high Vs. low energy) representing the other[21].
- Watson & Tallegena's Two-Dimensional Model (1985): This model suggests that emotions are divided into positive affect (such as joy, excitement) and negative affect (such as fear, sadness)[22].

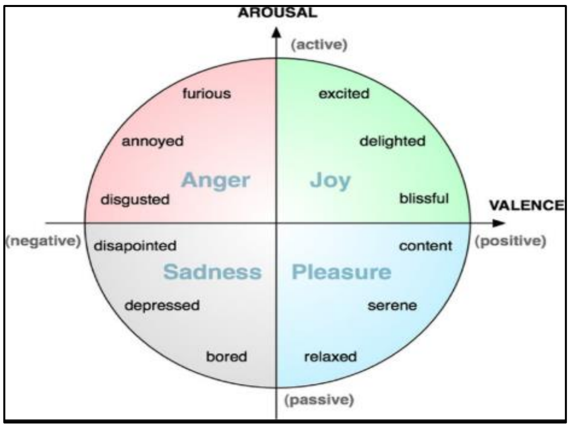

Figure1. 7 Two Dimensional Emotional Model [W8]

1.4 Components of Emotion

As we move through our daily lives, we experience a variety of emotions. Emotions are subjective states of being that, physiologically speaking, involve physiological arousal, psychological appraisal and cognitive processes, subjective experiences, and expressive behavior. Emotions are often the driving force behind motivation and are expressed and communicated through a wide range of behaviors[23].

But what exactly are emotions? Ah, a question that has puzzled philosophers and scientists alike for centuries! In psychology, emotions are generally understood as complex psychological states that involve four distinct components. These components work together to create a rich tapestry of our emotional lives, influencing everything from decision-making to our personal relationships[W9].

- **Subjanctive response:** Devide into:
  - **Verbal responses:** express themselves through speech or words. For example, saying "I am happy" or "I am sad" is a verbal response[W9].
  - **Nonverbal responses:** Nonverbal responses are expressed through facial expressions, body language, and tone of voice. For example, a smile is a nonverbal response to happiness, while tears can be a nonverbal response to sadness[W9].
- **Behavioral responses:** Behavioral responses are expressed through actions or behaviors. For example, hugging is a behavioral response to feelings of love, while screaming or hitting can be a behavioral response to anger[W9].
- **Physiological responses:** Physiological responses are expressed through changes in the body, such as changes in heart rate, breathing, and skin temperature. For example, feeling hot or red could be a physiological response to anger or embarrassment[W9].

Figure1. 8 Emotion's Components [W10]

1.5 Importance of Emotions in Human Life

Emotion play crucial role in human life, influencing decision –making, social interactions, and overall well-being .They help individuals respond to various situations by providing instinctive responses that guides behavior. Emotions also contribute to mental health, as the ability to recognize and manage emotions is linked to psychological resilience and emotional intelligence. Furthermore, emotions are essential for affective communication, enabling individuals to express their feeling and understand others trough verbal are nonverbal cues. Additionally, emotions shape memories and learning processes, as experiences with emotional significance tend to be more ingrained and impactful[24]~~.~~

Figure1. 9 Why Emotions are important [W11]

1.6 Conclusion

In this chapter, we have provided a brief overview of the basic concepts important for understanding our topic. Emotion recognition has been a focus of interest for many years, and many researchers have produced valuable research papers in this area. A selection of these works will be mentioned in the next chapter.

Chapitre 2 **Methods of Emotion Recognition**

2.1 Introduction

The study of emotions has moved from ancient Greek philosophy to modern neuroscience, where understanding them is crucial. According to contemporary research, emotions are closely linked to behavioral and physiological responses. This chapter introduces two prominent techniques in this field facial emotion recognition (FER) and remote photoplethysmography (rPPG), which offer a unique perspective on emotion analysis for practical applications.

2.2 Overview of Emotion Recognition

Emotion recognition is the process of identifying and interpreting human emotional states using various methods, such as body language, speech patterns, and facial expressions, as well as physiological indicators such as breathing and heart rate. Emotions are fundamental to human communication and impact decision-making, learning, and overall mental and physical health. The accuracy and scalability of emotion detection systems have increased with the development of artificial intelligence, machine learning, and sensing technologies[25].

Current emotion detection methods can be generally divided into four major classes:

- **Facial Expression Analysis:** utilizing computer vision to analyze the movements of facial muscles[26].
- **Speech Emotion Recognition:** using acoustics features such as pitch, tone and rhythm[27].
- **Text-Based Emotion Detection:** which employs Natural Language Processing to detect emotions in text[28].
- **Physiological Signal Based Detection:** the researchers monitor autonomic nervous system responses[29].

To improve dependability and context sensitivity, these modalities are frequently merged in multimodal emotion recognition systems. This allows for more human-like interactions in applications like virtual assistants, affective tutoring systems, mental health monitoring, and adaptive user interfaces.

In this work, we focus on physiological signal-based emotion detection using the rPPG CHROM method for contactless heart rate estimation and facial expression identification using DeepFace. This combination enables scalable, real-time multimodal emotion analysis.

Figure2. 1 Emotion detection abstract concept [W12]

2.3 Facial Emotion Recognition

Facial emotion recognition is a technique used to analyze emotions from various sources, such as images and videos, based on facial expressions. This technique belongs to a family of techniques known as "affective computing," a multidisciplinary field of research that addresses the ability of computers to recognize and interpret human emotional states, often relying on artificial intelligence technologies[30].

2.3.1 What is FER

FER, also known as facial expression recognition are forms of nonverbal communication that can be a meaningful gesture, a semantic signal, or a tone of voice in sign language. The idea of translating these emotional expressions has gained research interest in psychology, as well as in human-computer interaction[31-33].

Recently, the widespread availability of cameras and technological advances in biometric analysis, machine learning, and pattern recognition have played a significant role in the development of this technology[34]. As FER systems move from controlled laboratory environments to real-world applications, their integration with real-time processing and psychological emotion models, such as Ekman's six basic emotions, has become increasingly important[32]. Deep learning has proven particularly useful in this field, providing superior feature extraction capabilities and computational efficiency[35].

2.3.2 DeepFace

DeepFace is a deep learning framework for face recognition developed by Facebook. According to Taigman , its deep convolutional architecture was specifically designed to bridge the gap between the performance of machine learning systems and human-level face verification[36].

It is based on an artificial neural network (CNN) designed primarily for image recognition and processing, due to its ability to recognize patterns in images. This tool includes a complete library of state-of-the-art pre-trained models, making it the most efficient and lightweight model for facial expression and emotion detection [37].

DeepFace's application scope, has been extended by integrating it into multi-model emotion detection systems, which combine facial expression recognition with other data sources such as audio and physiological signals. It has become an essential tool in the field of emotion detection due to its powerful facial recognition capabilities and its ability to work seamlessly with other comprehensive emotion recognition systems[38].

- **Overview**

Our goal is to create a system that captures video from a webcam using the OpenCV library for computer vision tasks, along with DeepFace a deep learning library for face recognition and emotion analysis. The first step is to detect faces in each frame of the video feed. Once facial regions are identified, they are passed to DeepFace for emotion analysis, which uses deep learning models to predict the dominant emotions of each of the six Ekman emotions (Anger, surprise, Happy, Sad, Disgust, Fear and Neutral) for each detected face. Results Display: After face detection and analysis, the detected faces are labeled with rectangles, and the predicted emotions are applied to the video feed to provide real-time visual feedback on the detected emotions[W13].

Figure2. 2 Real-time Emotion Detection Using DeepFace [W13]

❖ How Does it work?

- Video Capture: We start by capturing a video from a webcam using OpenCV. Each frame is processed to identify faces and perform emotion analysis.
- Face Detection and Emotion Analysis: For each detected face, a region of interest (ROI) is extracted and analyzed using DeepFace. The model determines the dominant emotion detected in the face.
- Visualize the results: Using rectangles around the detected faces and displaying the predicted emotion on the video feed, this visual feedback helps us understand the participants' immediate emotional state . [W13]. As shown in the **Figure2. 3**

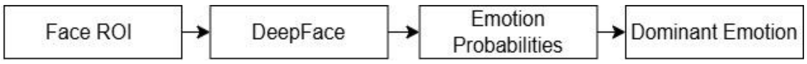

Figure2. 3 FER Analysis

2.3.3 Applications of FER

Facial expression recognition (FER) methods using computer vision, deep learning, and artificial intelligence have grown tremendously over the past few years due to their well-known applications in security lectures, medical rehabilitation , FER in the wild, and safe driving[39, 40] .

Numerous studies have been conducted on this topic including proposals techniques and networks, opinion polls. Computer generated real time facial emotion recognition mimics human coding skills, conveying important cues that complement speech to assist listeners. Similarly, the latest development focuses on deep learning and AI using edge units to ensure efficiency[41].

Figure2. 4 FER Applications[W14]

2.4 Remote Photoplethysmography-rPPG

Over the past decade, remote measurements of human vital signs have received increasing attention in the research community. Remote Photoplethysmography (rPPG) has emerged as a promising optical technology in the quest for non-contact measurement of physiological parameters. By analyzing light absorption and reflection patterns, rPPG enables remote extraction of vital signs , such as heart rate , remotely and without physical contact with the subject. PPG is the core technology upon which IPPG is based. Therefore, introducing the basic concepts related of IPPG and demonstrate the evolution of this non-contact technology[42-44].

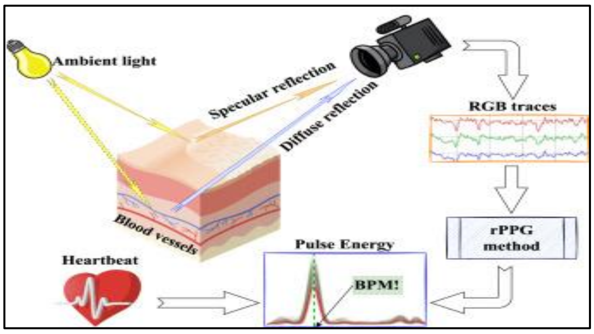

Figure2. 5 Pulse signal of rPPG method is uses signal processing to extract heartbeat information [W15]

2.4.1 Historic of rPPG

Photoplethysmography (PPG) is changing the way we view health and wellness. Initially observed in 1938s, By Ulrich B. Hertzman, who introduced the term “Photoelectric plethysmography” and suggested that it represented the volumetric changes(“plethysmo” means”enlargement” in Greek)[45].PPG is a simple and low-cost optical bio-monitoring technique used to non-invasively measure the blood volume changes that occur in the mesure blood volume changes[46]. In PPG, using an e example of wearable, such as a heartrate-sensing watch, as shown in the **Figure2.6** below .It works by emitting light onto the skin and measuring the amount of light reflected back, this changement in light indicate variations in blood volume, allowing estimation of heart rate[47].

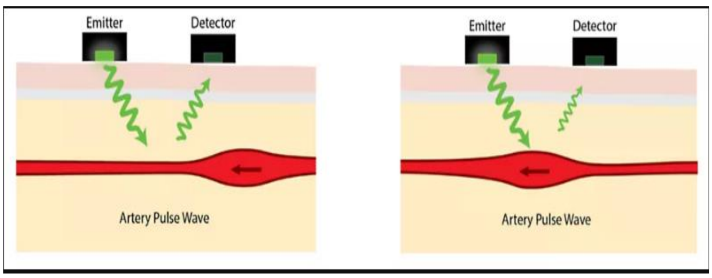

Figure2. 6 Optical heart rate sensing [W16]

rPPG envolved from contact-based PPG. It is an emerging, non-invasive method that estimates physiological parameters, most notably heart rate, by analyzing subtle color changes in facial skin captured by a camera. This technology is based on conventional photoplethysmography (PPG), which measures blood volume changes using light, but expands its usefulness by eliminating the need for direct skin contact, making it ideal for real-world, contactless monitoring[48].A multi-wavelength RGB camera is used by rPPG technology to identify minute variations in skin color on the human face caused by changes in blood volume during a heartbeat, as illustrated in **Figure2.7** .

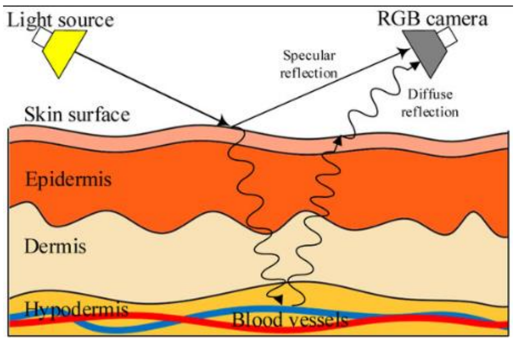

Figure2. 7 Schematic diagram of rPPG technology [W17]

2.4.2 How rPPG works

The process of extracting vital signs from video is complex and involves several carefully designed steps. Firstly, A standard camera is used to record video of the person, focusing on areas such as the face where blood volume changes are most evident. Secondly, once the video is captured, a specific Region Of Interest (ROI) is selected. This usually involves selecting an area of the face, as it provides a steady, clear view of the skin. Advanced computer vision algorithms can automatically detect and track the region of interest across frames, even if the person is moving. Thirdly, Signal extraction involves analyzing pixel intensity changes over time within a specified region of interest. Specialized signal processing techniques filter out noise caused by motion, lighting changes, or other environmental factors. This step is crucial to isolate the pulse signals in the video data. Lastly, the extracted signals are processed, by detecting peaks, inter-beat intervals are measured and then the heart rate, are estimated[49, 50].

Each stage contributes to the overall reliability and accuracy of the rPPG system, ensuring it operates efficiently in a variety of environments and conditions.

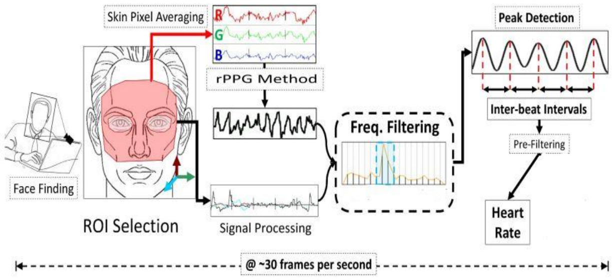

Figure2. 8 Schematic overview of rPPG pipeline [W18]

2.4.3 Methods of rPPG

This technology has gained significant popularity as a non-contact method for physiological measurements, particularly heart rate estimation from facial videos. The main categories of rPPG include color-based, motion-based, multispectral, depth-based, and mixed or hybrid methods[W19].

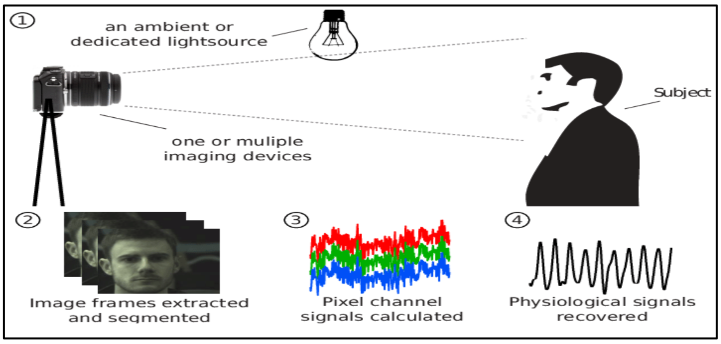

Figure2. A survery of remote optical photoplethysmography grafic imaging methods [W20]

❖ **Robust Pulse Rate from Chrominance- CHROM**

In our project, we choose The Chrominance Method **CHROM** [51]. It has been proposed to address the weakness of other methods, as it enhances against motion robustness. The CHROM method leverages the unique characteristic of facial skin color changes, which are caused by alterations in the cardiac cycle, and can be more pronounced than variations in intensity. CHROM depending on two orthogonal chrominance vectors $\mathbf{X}_{\mathrm{CHROM}}$ and $\mathbf{Y}_{\mathrm{CHROM}}$ [52]. The two vectors are calculated as follows, with r,g, and b representing the respective channels:

$$X_{CHROM}(t) = 3x_r(t) - 2x_g(t) \ldots\ldots\ldots\ldots\ldots\ldots..(2.1)$$

$$Y_{CHROM}(t) = 1.5x_r(t) + x_g(t) - 1.5x_b(t) \ldots\ldots\ldots\ldots\ldots\ldots..(2.2)$$

The final rPPG signal is then calculated as:

$$\mathbf{s}(\boldsymbol{t}) = \boldsymbol{X}_{\boldsymbol{CHROM}}(\boldsymbol{t}) - \boldsymbol{\alpha}\,\boldsymbol{Y}_{\boldsymbol{CHROM}}(\boldsymbol{t}) \quad \dots\dots\dots\dots\dots\dots..(\mathbf{2.3})$$

Where:

$$\boldsymbol{\alpha}(\boldsymbol{t}) = \frac{\boldsymbol{X}_{\boldsymbol{CHROM}}(\boldsymbol{t})}{\boldsymbol{\alpha}\,\boldsymbol{Y}_{\boldsymbol{CHROM}}(\boldsymbol{t})} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{2.4})$$

σ() is the standard deviation, the parameter **α** accounts for imprecision in skin-tone standardization.

Depending on the chosen method, the pulse signal retrieval algorithm, can be divided into several steps. Start by extracting skin tone cues signals from the video sequence, then projecting the average skin color in the specified chrominance space using Bandpass filtering in the [0.7-4 Hz] color space. This ends up building the pulse signal[W21].

To be more specific ; The filer is used to isolate the pulse signals and analyzed via peak detection to extract Heart beats every 30 Frames Per Second (FPS), because we relied on 29 frame delay time steps [53]. That why we get HR=0 in this period which the PPG needs 1 second of stable signal to temporary storage, the purpose is getting the heart rate estimation.

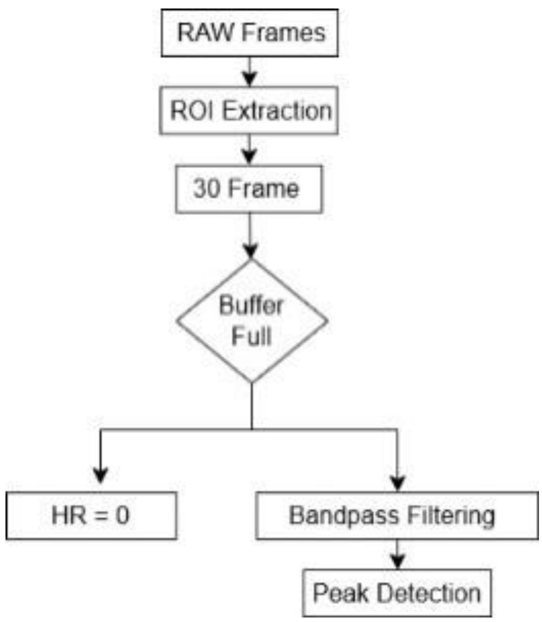

Figure2. 10 HR Estimation

Firstly, we identifies the heart beat timestamps in the filtered signal, in order to have the Inter Beat Interval (IBI),which is the time between peaks ,that measured in seconds[54] .Using the flowing equation :

$$\mathbf{IBI} = \frac{\text{difference of peaks}}{\mathbf{30}} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{2.5})$$

As a result, to obtain the Beats Per Minute (BPM):

$$\mathbf{BPM} = \frac{60}{\boldsymbol{IBI}} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{2.6})$$

Which it is represent the Heart Rate.

<u>For Example:</u>

Peaks: detect at frames 30, 54, 78 → peaks at t=1s

IBIs: [0.8s, 0,8s] ←→ from

$$\mathbf{IBI} = \frac{(\mathbf{54} \ - \mathbf{30})}{\mathbf{30}} \ = \ \mathbf{0.8}$$

$$\mathbf{BPM} = \frac{60}{\mathbf{0.8}} \ = \ \boldsymbol{75\ BPM}$$

Figure2. 11 HR Measurement

In general, rPPG methods consist of various strategies, each with its own principles, benefits, and uses. rPPG is evolving as a useful tool for non-invasive physiological monitoring in multiple fields.

2.4.4 Applications of rPPG

With rapid advances in research and technology, rPPG methods have found applications in diverse fields beyond remote heart rate measurement, providing compelling evidence of their research potential and application prospects. These systems are increasingly being used in healthcare, education, gaming, and human-computer interaction to provide emotion aware responses[49, 55]. This technology has opened up new horizons in affective computing.

2.5 Limitations of Unimodal Emotion Systems

Unimodal emotion recognition has limitations in accurately detecting human emotions because of its reliance on a single dataset to detect emotions, which can lead to potential inaccuracies [56, 57]. These systems often struggle due to:

- **Expressional Ambiguity:** A single facial expression can convey multiple emotions, leading to misinterpretations.
- **Environmental and Individual Variability**: Sensitivity to factors such as lighting and individual differences impacts accuracy.

2.6 Multi-modal Fusion in Emotion Detection

This approach combines data from multiple modalities, such as facial expressions, physiological signals, etc., providing a solution to these limitations and enabling a more comprehensive and accurate analysis of emotions[57, 58].The concept of multimodal integration:

- **Data integration:** Multimodal integration combines diverse data sources to capture different emotional aspects, providing a comprehensive analysis.
- **Complementary insights**: Each pattern provides unique information that complements the others, leading to richer emotional understanding.
- **Robustness and accuracy:** Combining patterns enhances the robustness and accuracy of the system, and addresses variability and ambiguity in emotional expressions.

2.7 Conclusion

Today, it has become possible to discover and measure various aspects that define the nature of emotions. However, this discovery is incomplete, due to the complexity of signals on the one hand and the diversity of individuals on the other. There is no comprehensive model for identifying emotions. However, many studies have focused on collecting data to improve this model. To achieve this, in the next chapter, we will review how emotions are identified through various means.

Chapitre 3 **Methodology and Architecture System**

3.1 Introduction

Emotion recognition is a fundamental component of affective computing. Therefore, when designing an emotion recognition system that enables real-time monitoring of a user's emotional states by combining two modalities. In this chapter, Starting from the various steps and tools used in the development environment to displaying the various results obtained, including screenshots of our application.

3.2 System Overview

The proposed system focuses on an innovative approach that integrates facial expressions with physiological signals to achieve a comprehensive understanding of emotions, leveraging the complementary strengths of each data source to improve the system's accuracy and efficiency in real-time scenarios. This enables us to explore new possibilities for intelligent systems capable of better responding to human emotions.

This project aims to develop an innovative simulator that enables facial analysis and heart rate estimation based on rPPG. This demonstrates the behavioral interaction between a human user and a visual interface (GUI). This allowed us to classify emotions into seven categories: anger, disgust, fear, joy, neutral, sadness, and surprise.

3.3 System Architecture

We adopted a standard structure consisting of an input section, a processing section for integrating data, and an output section for immediate display in an interactive window.

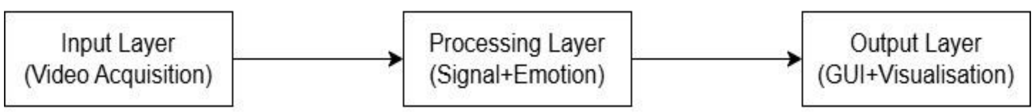

Figure3. 1 System Architecture Overview

3.4 Implementation

We will present various work environments that illustrate a framework for multimedia impact, application implementation, and user experience enhancement, highlighting the effectiveness of the graphical interface for ease of use and visual interpretation.

3.4.1 Hardware Specifications

The configuration of the machine used in our project is shown in the **Table3.1** below.

CPU	Intel Core I5-8365U CPU with Frequency of 1.60 GHz and up to 1.90 GHz
Operating System	Windows 10, 64 bit
RAM	8.00 GB
Webcam	Width: 640.0/ Height: 480.0/ FPS: 30.0

Table3. 1 Device Datasheet

3.4.2 Software Requirements

In this study, we used specific software environments to facilitate the development, simulation and testing of the proposed system.

1. **Programming Language**

Python is a powerful programming language known for its simplicity and readability. Developed by Guido van Rossum in 1991, Python has evolved into the preferred choice for a wide range of applications, from web development to data science.It's history, features, and advantages make it a versatile and powerful programming language. Its readability, extensive libraries, and active community support make it an excellent choice for developers in various fields and beyond[W22,W23].

Figure3. 2 Python [W24]

2. Development environment

Thonny is a new IDE for learning Python programming that enables beginners to naturally visualize programs. It was introduced in 2015, by Aivar Annamaa of the University of Tartu in Estonia.Its notable features include different ways to explain code, step-by-step expression evaluation, an intuitive visualization of the call stack, and a mode for explaining the concepts of references and the heap. Supports educational research by recording user actions to replay or analyze the programming process. It is free to use and expandable[59].

Figure3. 3 Thonny IDE [W25]

3.4.3 Libraires

In this project, several libraries were used, including:

- OpenCV

OpenCV (Open Source Computer Vision Library) is a library of programming functions mainly for real-time computer vision. Originally developed by Intel, it was later supported by Willow Garage. It features GPU acceleration for real-time operations[60].

Figure3. 4 OpenCV [W26]

- DeepFace

Deepface is a lightweight facial analysis framework including face recognition and demography (age, gender, emotion and race) for Python. You can apply facial analysis with a few lines of code. It plans to bridge a gap between software engineering and machine learning studies[61].

Figure3. 5 DeepFace [W27]

- PyQt5

PyQt5 is a set of Python bindings for the Qt application framework, extensively used for developing cross-platform GUI applications. It provides a wide range of tools and features to create professional and modern user interfaces[62].

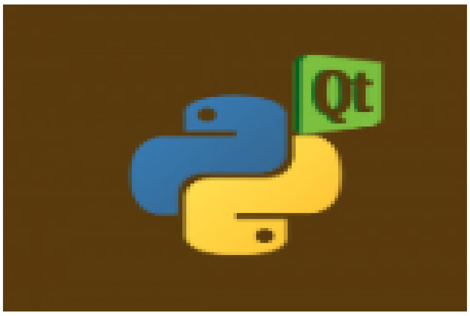

Figure3. 6 PyQt5 [W28]

- Pandas

Pandas are a fundamental Python library renowned for its capabilities in data manipulation and analysis. Specifically designed for working with structured data, Pandas excels in tasks such as data cleaning, transformation, and aggregation[63].

Figure3. 7 Pandas [W29]

- Numpy

The name "Numpy" stands for "Numerical Python". It is the commonly used library. It is a popular machine learning library that supports large matrices and multi-dimensional data. It consists of in-built mathematical functions for easy computations[64].

Figure3. 8 Numpy [W30]

- Scipy

The name "SciPy" stands for "Scientific Python". It is an open-source library used for high-level scientific computations. This library is built over an extension of Numpy. It works with Numpy to handle complex computations, allows to sorting and indexing of array data, the numerical data code is stored in SciPy. It is also widely used by application developers and engineers[65].

Figure3. 9 Scipy [W31]

3.4.4 Datasets

To assess the system with accuracy, experiments were performed using two datasets commonly used in the field of emotion recognition.

- **FER 2013**

The dataset contains images along with categories describing the emotion of the person in it. The dataset contains 48×48 pixel gray scale images with 7 different emotions such as Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The dataset contains 28709 examples in the training set, 3589 examples in the public testing set, and 3589 examples in the private test set[W31].

Figure3. 10 FER Dataset [W32]

❖ **Emotions and Heart rate scale classification-DEAP**

It is Database for Emotion Analysis using Physiological Signals. It is a well-known publicly available dataset that includes physiological and emotional data collected from participants while they were exposed to audiovisual stimuli. By using the DEAP dataset, we can explore the relationship between emotions and heart rate, analyze the physiological responses associated with different emotional states, and develop models for emotion recognition or prediction based on heart rate data[W32].

Emotion	Min HR(BPM)	Max HR(BPM)	Optimal HR(BPM)	HR Std Dev
Angry	80	120	95	10
Disgust	75	110	90	8
Fear	85	130	105	12
Happy	65	100	80	7
Sad	60	90	75	8
Surprise	82	125	100	11

Table3. 2 HR Dataset [W33]

3.5 Methodology

In our Multimodal emotion recognition system, we device our work into three sections:

1. Source Input.
2. Parallel Processing Pipelines: To handling multiple data streams simultaneously to reduce latency and improve throughput.

- Facial Expression Recognition Pipeline.
- Heart Rate Estimation Pipeline.
- Multimodal Fusion.

This system is designed to analyze emotional states and physiological responses in real time. The general idea is illustrated in the **Figure 3.11** below.

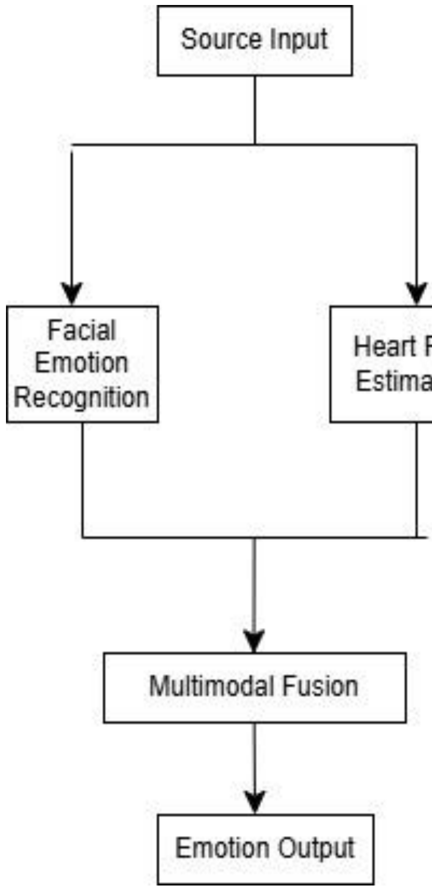

Figure3. 11 Block Diagram

3.5.1 Block Diagram Component

In this project, we proposed a contactless emotion recognition system that combines facial expression analysis using DeepFace and the colorimetric method (CHROM) to estimate the rPPG physiological signal. The methodology of our system follows a structured pipeline that starts by selecting source Input, which include (webcam/pre-recorded video), then activating the feed via an OpenCV interface, which generates an instantaneous video stream at 30 frames per second for real-time processing. Once the video is captured, a parallel processing occurs.

The system's analysis begins by identifying the face using Deepface and regions of interest (ROIs) across the forehead and cheek areas, which are dynamically adjusted according to facial movements and optimized to extract RGB signals continuously each frame.

The facial expression analysis, use DeepFace framework a powerful pre-trained tool by detecting seven universal expressions;(anger, happiness, fear, surprise, disgust, and neutral) for classifying the dominant emotion with the highest probability which directly extracts the probabilities of emotional states in the output. Meanwhile, in the heart rate estimation using CHROM-based rPPG, a non-contact technology by tracking color changes in facial areas. The process begins with extraction from ROIs, where RGB signals are averaged across such as the forehead and cheeks. The signal is then processed through color calculations using the **Eqt(2.3)** and bandwidth filtering (0.7–4 Hz, corresponding to 42–240 beats per minute) to isolate the frequencies associated with pulses .The peaks are then detected from signal. We identifies the heart beat timestamps in the filtered signal to isolate the pulse signals and analyzed via peak detection to extract Heart beats every 30 Frames Per Second (FPS), because we relied on 29 frame delay time steps . That why we get HR=0 in this period which the PPG needs 1 second of stable signal to temporary storage in order to have the Inter Beat Interval (IBI) according to **Eqt(2.5)** , which is the time between peaks that measured in seconds to obtain the Beats Per Minute (BPM) calculated using **Eqt(2.6)** defining the Heart Rate.

The outputs from both methods are combined via multimodal fusion, implementing a new strategy that combines facial emotion probabilities with heart rate emotion mappings from the Kaggle dataset to generate the final emotion output. Using the weighted combination, the system calculates an overall score by multiplying the facial recognition probabilities by 0.6 and the heart rate probabilities by 0.4, then normalizing the results. This result is subsequently used for Visualization and Data Storage, enabling both real-time emotional feedback and archiving allowing for accurate physiological monitoring compatible with emotional analysis.

3.6 Real time Implementation

We present a framework that defines the multimodal fusion of physiological and behavioral parameters in a realistic scenario, where the previously proposed algorithm is integrated into a graphical user interface to test its validity on the collected multimodal data.

3.6.1 User Interface Design

In our system design, there is a effective perception window which represents the main analysis contains a left panel for camera/video feeding and RGB signal plots. The right panel consists of a control panel for selecting the source, as well as start/stop buttons for analysis, entering the subject's name and signal quality index, displaying results including facial expressions and aggregated probability bars. Window of heart rate and peak detection chart, an additional window for viewing the recorded data. The interface is illustrated in **Figure 3.12** below.

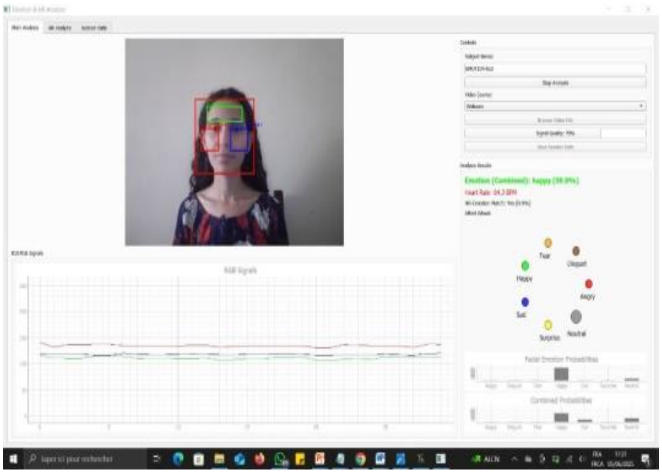

Figure3. 12 GUI'S Interface

3.6.2 How to use It?

The graphical user interface includes a control panel with different to facilitate user interaction with results tracking and signal quality. Options include taking a break or ending the session with saving the data.

The system

The system displays the collected after analyzed results, providing real time an intuitive representation of a person's emotional and physiological state. Data is saved throughout the session to a summary file of the obtained results. The general project mechanism can be summarized in the flowchart below ensures accurate and immediate analysis while maintaining a user-friendly interface, as shown in **Figure 3.13**.

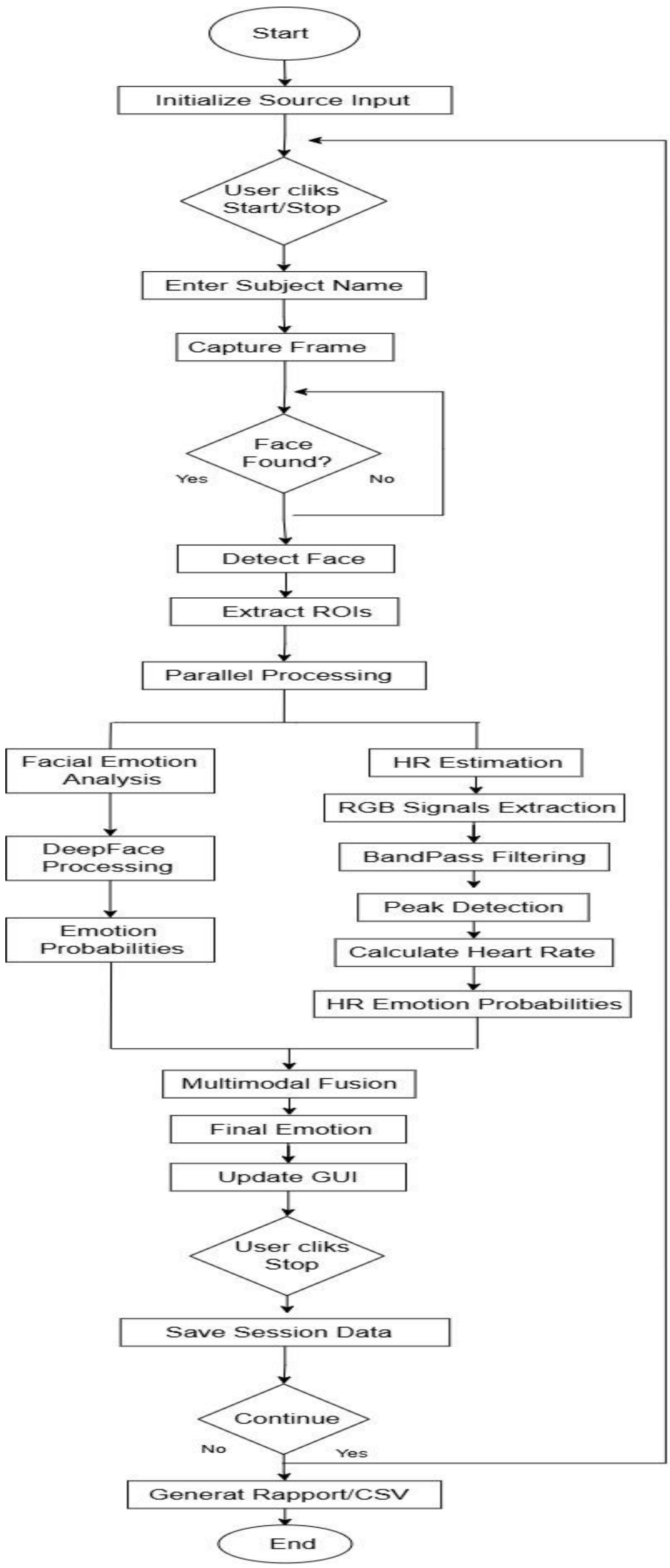

Figure3. 13 Flowchart

3.6.3 Data Logging

Data is saved, on CSV File Structure. Each session is saved with (Timestamp, HR, signal quality, Detected emotion and confidence, Raw RGB signals from ROIs).

- Data is saved in sessions **[subject_name]/[date]** directory.
- Includes a summary file with session statistics.
- Video recorder and PDF File.

3.7 Results and Evaluation

Before jumping into the Results, an evaluation metrics for the Emotion analysis task to assess the effectiveness of the model [W34]. Let's define these terms:

- **Accuracy:** The proportion of correctly classified instances out of the total instances.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{3.1})$$

- **Precision:** Out of all instances predicted as positive, how many are actually positive.

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{3.2})$$

- **Recall:** Out of all actual positive instances, how many were correctly predicted as positive.

$$\text{Recal} = \frac{TP}{(TP + FN)} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{3.3})$$

- **F1 Score:** The harmonic mean of precision and recall. Provides a balanced measure when there is an uneven class distribution.

$$\text{F1 Score} = \frac{Precision\ \ Recall}{(Precision + Recall)} \quad \dots\dots\dots\dots\dots\dots..(\mathbf{3.4})$$

The confusion matrix is essential to understanding precision and recall. Here's a basic structure:

- **True Positive (TP):** Correctly predicted positives instances.
- **False Positive (FP):** Incorrectly predicted positives instances (Type I Error).
- **False Negative (FN):** Missed positives instances (Type II Error).
- **True Negative (TN):** Correctly predicted negatives instances.

By mastering these metrics, we’ll gain better insights into our model’s performance, we will see that next.

3.7.1 Description of Session Summary

The report, represents an "Emotion & HR Analysis " for the "EMOTION-test" subject, identified by Session **ID 20250605_172727**, was generated on **June 05, 2025**. It encompasses analysis data, video recording, and plots.

Here's a breakdown of the key metrics:

- **Duration**: The session lasted 65.6 seconds.
- **Average HR:** The average heart rate was 78.7 beats per minute (bpm), with a range from 0.0 to 109.1 bpm.
- **Dominant Emotion:** The dominant emotion recorded during the session was Happy.
- **Average Signal Quality:** The average signal quality was 62.6%.
- **HR-Emotion Match Rate:** The heart rate and emotion match rate was 92.9%. Which indicating strong alignment between HR and detected emotion.

3.7.2 Graphical Representations

The proposed project is the beginig of an interesting application in the field of computer vision and deep learning, using facial expressions to gain deep insights into emotions. We will explore the various tools and libraries used.

1. RGB Signals from Facial ROIs

The graph is showing RGB signals from facial regions of interest (ROIs) over time, as shown in the **Figure3.14**. The x-axis represents time in samples, and the y-axis represents intensity ranging from 0 to 255. There are three.

The red signal starts with a high intensity, experiences a sharp drop, and then fluctuates around a value between 130 and 140, it shows a gradual decrease toward the end of the time period. The green signal starts with a low intensity, experiences a sharp increase, and then fluctuates around a value between 110 and 120, it shows a dip towards the end. The blue signal starts with a low intensity, experiences a sharp increase, and then fluctuates around a value between 120 and 130,t shows a significant dip towards the end.

The graph shows that the red channel is the most dominant, with the highest intensity values throughout the time period. The green and blue channels show similar patterns, with both starting low and increasing before fluctuating around a lower intensity. The fluctuations in the signals could be due to various factors, such as changes in the light source or the facial regions being analyzed.

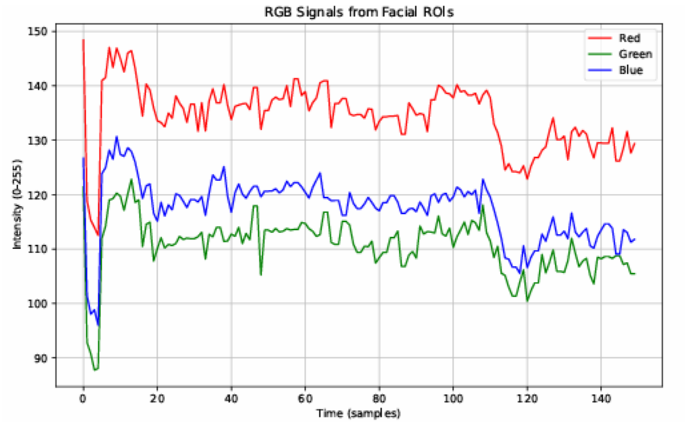

Figure3. 14 RGB Signals

2. Heart Rate Signal

As shown in **Figure 3.15**, a red line displays the fluctuations in heart rate signal over time, measured in beats per minute (BPM) The x- axis represents time in samples, and the y-axis represents the HR in BMP. We can device it into three phases, as following:

Initial Spike (Samples 0-50);the heart rate starts at 0 BPM and rapidly increases to over 100 BPM within the first 50 samples. Fluctuating Heart Rate (Samples 50-1750);the heart rate fluctuates between approximately 60 and 100 BPM throughout the majority of the signal, there are periods of relative stability and periods of more rapid changes. Decreasing Heart Rate (Samples 1750-2000);towards the end of the signal, the heart rate gradually decreases, settling to around 60 BPM, this suggests a return to a resting or more relaxed state.

The heart rate signal exhibits normal variability .These patterns are typical of a healthy heart rate in response to different conditions. The initial spike could be due to the start of an activity, and the final decrease could be due to the end of the activity. The fluctuations in between could be due to the body adjusting to the activity and other physiological factors.

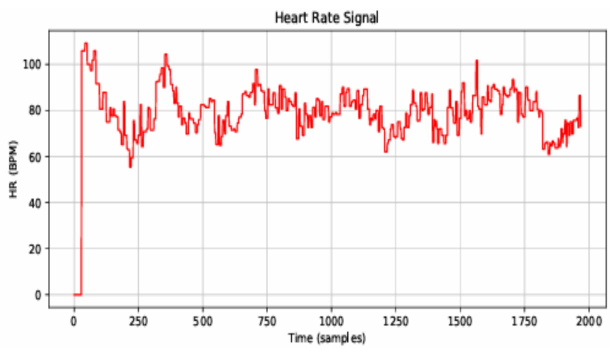

Figure3. 15 HR Signal

3. Filtred Signal with Peak Detection

Here; in the **Figure 3.16** above, a blue line depicts the filtered signal, showing fluctuations over time. Red dots mark the peaks of the signal. The x-axis represents "Time (samples)" ranging from 0 to 2000, while the y-axis represents "Amplitude" ranging from -1.5 to 1.0.

The signal has been processed to isolate unwanted noise using a Bandpass filter. This can be done because a heartbeat is usually between 0.7 and 4.0 Hz. These dots show where the signal is strongest. It is often used to identify important changes in the signal.

This type of visualization is commonly used in signal processing to analyze and understand the characteristics of signals.

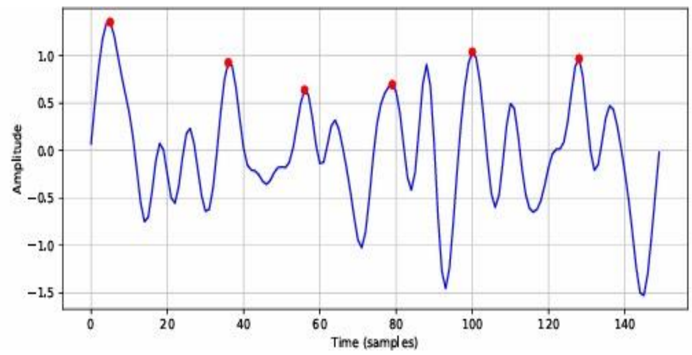

Figure3. 16 Filtred Signal with Peak Detection

4. Emotion Distribution

A bars Chart represent, in **Figure 3.17**, which is displaying the probability percentages of different emotions.The x-axis lists emotions: "angry," "disgust," "fear," "happy," "sad," "surprise," and "neutral." The y-axis shows the probability percentage from 0 to 100.

Here's a breakdown detailed; Happy,has the highest probability, indicated by the tallest green bar, at around 60%.Sad,the blue bar, reaching almost 20%.Angry, Fear, and Neutral, indicated by red, orange, and gray bars respectively , they have the moderate probabilities, all about 10%.Disgust, with the lowest probabilities , below to 10%. While, surprise: has a neglibigle probability 0%, indicated by the absence of a bar. The chart shows that the dominant emotion is "Happy" while "Disgust" is the least.

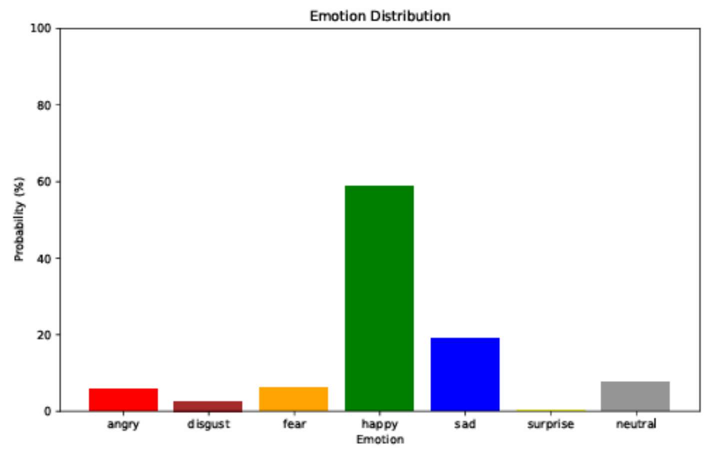

Figure3. 17 Bar Chart illustrating the probability distribution of different emotions

5. HR vs Dominant Emotion

As shown in **Figure 3.18;** a scatter plot visualizes the relationship between heart rate, and persentage of dominant emotion The x-axis represents heart rate in beats per minute (BPM), ranging from 0 to 100. The y-axis represents emotion probability, ranging from O to 60. Different emotions are represented by different colors: angry (red), disgust (purple), fear (orange), happy (green), sad (blue), and neutral (gray).

Each dot on the plot represents a data point where a certain heart rate was measured, and the corresponding dominant emotion was identified. key observations include:

- Happy: primarily associated with higher heart rates, mostly clustering around 60 BPM and above and with an emotion probability near 60%
- Sad: generally occur with heart rates between 60 to 100 BPM, with an emotion probability near 20%.
- Neutral: observed at heart rates ranging from 60 to 100 BPM, with an emotion probability near 8%.
- Fear: observed at lower heart rates around 0 and 70 BPM, with an emotion probability 7%.
- Angry: observed at heart rates ranging from 64 to 100 BPM, with an emotion probability around 7%.
- Disgust: observed at heart rates ranging from 78 to 90 BPM, appears to have a low probability near 3%.

The plot illustrates how heart rate can be a physiological indicator of different emotional states.

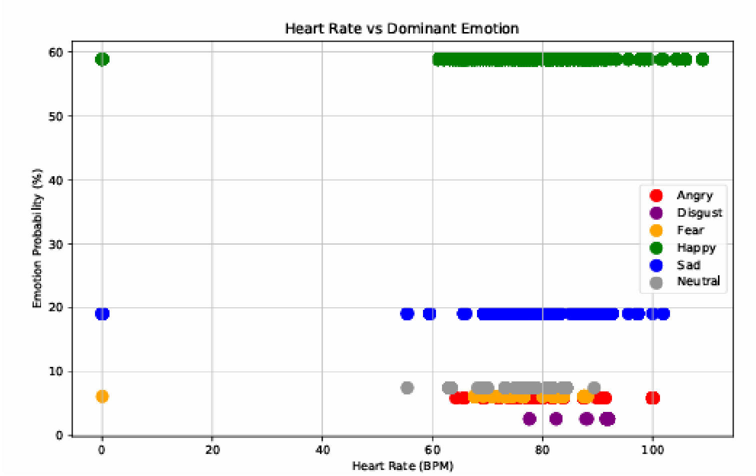

Figure3. 18 Scatter Plot showing the relationship between heart rate (BPM) and dominant emotion probability(%)

6. The Three Confusion Matrices

Each depicting the performance of different models in classifying emotions: "Face Only," "HR Only," and "Combined." The matrices are color-coded, with darker shades of blue indicating higher values, representing the number of instances where a predicted emotion matches the true emotion. Starting with the Confusion Matrices as shown in the **Figure3.19** below;

- **(1)Face-Only Confusion Matrix :** The diagonal entries indicate correct classifications, with 99 instances of "angry," 75 of "fear," 1,228 of "happy," and 90 of "neutral." The off-diagonal values reveal misclassifications, such as "disgust" being mistaken 24 times for other emotions. This suggests that facial features alone perform well in distinguishing emotions but still exhibit some classification errors.

- **(2)HR-Only Confusion Matrix :** The pattern differs significantly from the face-only approach. The diagonal values indicate 277 correctly classified instances of "sad," 411 of "happy," and 324 of "neutral/surprise." However, the off-diagonal entries are generally higher than in the face-only matrix, showing more frequent misclassifications. For example, "angry" is often confused with "disgust" 17 times, highlighting the limitations of HR-based classification when used independently.

- **(3)Combined Confusion Matrix :** The combined model demonstrates higher diagonal values with 1,228 correct classifications for "happy," 75 for "fear," and 90 for "neutral." Compared to the HR-only matrix, the combined approach achieves higher accuracy, with improved diagonal values and fewer off-diagonal misclassifications. For instance, the number of misclassifications for "angry" is reduced to 110, and "disgust" is only misclassified 24 times.

Overall,this indicates that combined approach the most effective for classification. This highlights the complementary nature of these modalities in capturing emotional states comprehensively.

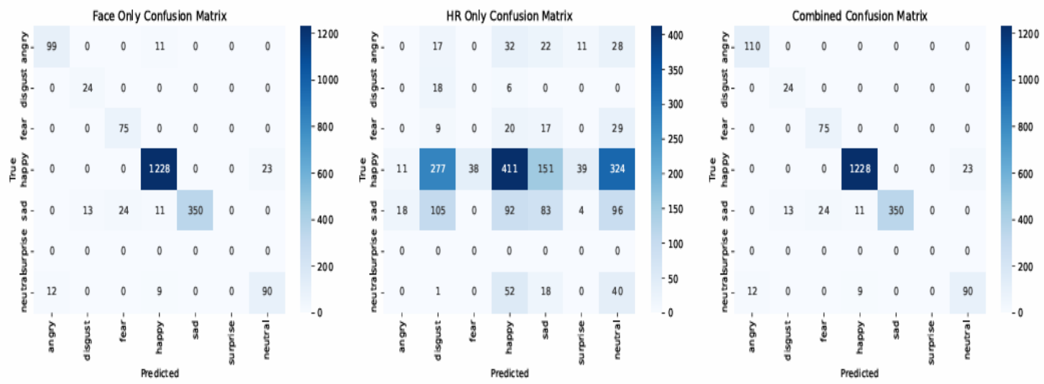

Figure3. 19 Confusion Matrix -(1) Face Only , (2)HR Only, (3)Combined

7. Performance Metrics

The table presents performance metrics summary, which is comparing three different methods,"Face Only", "Hr Only", and "Combined", as shown in **Table3.3**. Using the four evaluation metrics.

Based on the data. The "Face Only" achieves high scores across all metrics, with values around 0.948-0.953.The "Hr Only" method shows significantly lower performance, with scores around 0.280-0.489..While , the "Combined" slightly outperforms the "Face Only" method, with scores around 0.953-0.959.

Method	Accuracy	Precision	Recall	F1 Score
Face Only	0.948	0.953	0.948	0.949
Hr Only	0.280	0.489	0.280	0.337
Combined	0.953	0.959	0.953	0.954

Table3. 3 Performance Metrics Summary

The graph displays a bar chart comparing the performance metrics of three different methods, which it helps to visually compare the performance of the different methods, the combined method has the best performance, as illustrated in **Figure3.20** below.

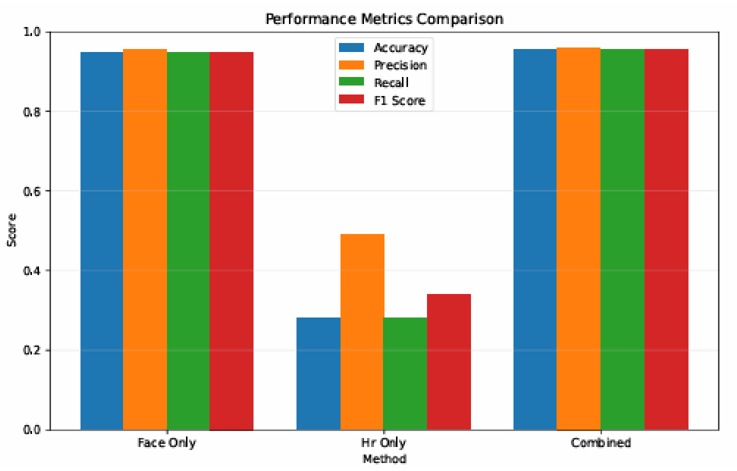

Figure3. 20 Performance Metrics Comparaison

3.8 Discussion

Based on the provided report, the results demonstrate a highly successful multimodal approach to emotion detection, with a notably strong correlation between heart rate and facial emotion recognition. The combined method achieved perfect accuracy , close to 1.000 across all metrics, indicating a well-optimized fusion of physiological and visual cues. In contrast, heart rate analysis alone yielded poor classification performance (accuracy: 0.280), reinforcing the necessity of integrating facial features for robust emotion recognition.

3.9 Conclusion

The results of this study confirm the effectiveness of hybrid approaches in emotion recognition, particularly for enhancing classification accuracy and system reliability in unconstrained environments. Furthermore, the work aligns with ongoing efforts in the scientific community to move from unimodal to context-aware and user-sensitive emotion recognition systems.

Despite its strengths, the system has certain limitations, such as sensitivity to fast head movement or extreme lighting variations, and limited support for emotions that are subtle or culturally variable. These aspects provide a foundation for future research and improvement.

General Conclusion

The ability to detect and understand human emotions is a key component in the development of intelligent systems. This proposing project implemented a multimodal, contactless emotion recognition system that combines face detection and expression analysis using DeepFace technology with physiological signal estimation using CHROM-based remote photoplethysmography (rPPG). This combination of these techniques addresses many of the limitations of traditional single modality emotion recognition methods and represents a significant step forward in affective computing and human-computer interaction.

This research relies on combining facial visual cues with physiological signals to infer emotional states more accurately than using facial features alone. The entire system is designed to operate in real-time using standard video inputs, without the need for any physical sensors or wearable devices, making it ideal for applications requiring non-intrusive monitoring, such as telemedicine, driver attention monitoring, and smart environments.

The system demonstrates improved robustness under common real-world challenges, such as poor lighting, partial facial occlusions (such as glasses or masks), and subtle motion and sensitivity to rapid head movement and limited support for subtle or culturally variable emotions. This resilience is critical for practical applications where ideal conditions cannot be guaranteed. The results of this study confirm the effectiveness of hybrid approaches for emotion recognition, particularly in improving classification accuracy and system reliability in unconstrained environments. Furthermore, this work aligns with ongoing efforts in the scientific community to transition from single-modality emotion recognition systems to context-aware, user-sensitive emotion recognition systems; Our methodological choices clearly bear fruit, particularly in validating the integration of DeepFace and CHROM-based rPPG ,these aspects provide a foundation for future research and improvements.

Despite the system's strengths and promising results, there are some limitations. Improving preprocessing techniques, such as motion in facial analysis and noise filtering in heart rate signals, would improve the system's real-time performance. Future improvements may explore alternative deep learning-based rPPG techniques, with the potential to incorporate other multimodal data, improve real-time pipeline optimization, and applay parallel computing strategies with GPU acceleration to become more feasible. Future work will include developing models capable of effective emotion recognition across different cultures and languages, ensuring the universality and broader applicability of emotion recognition systems. The achieved optimal classification indicates strong potential for practical applications in areas such as affective computing, human-computer interaction, and personalized user experiences.

In terms of practical applications, the developed system can be adapted for a variety of purposes In mental health, it could be used as a passive monitoring tool to detect early signs of stress, anxiety, or depression. In education this could help intelligent teaching systems adapt to students' emotions and improve their engagement, also to detect driver fatigue or emotional distress in the automotive context . In intelligent assistants, interactions could become more natural and empathetic.

In conclusion, this research demonstrates that a real-time multimodal approach using DeepFace and rPPG provides a more comprehensive, accurate, and user-friendly solution for emotion recognition compared to single-modality methods. By bridging the gap between physiological and visual emotional cues, the proposed system contributes to the development of emotionally intelligent machines capable of understanding and responding to human emotions in real-world contexts. The methodology, results, and tools developed through this research pave the way for future innovations in emotion-aware computing systems.

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