Emotion Detection using Electrocardiogram and Machine Learning Techniques : A Review

Chaminie De Silva
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e16070@eng.pdn.ac.lk

Damsy De Silva
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e16069@eng.pdn.ac.lk

Shamra Marzook
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
e16232@eng.pdn.ac.lk

Roshan Ragel
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
roshanr@eng.pdn.ac.lk

Isuru Nawinne
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
isurunawinne@eng.pdn.ac.lk

Mahanama Wickramasinghe
Department of Computer Engineering
University of Peradeniya
Peradeniya, Sri Lanka
mahanamaw@eng.pdn.ac.lk

Suranji Wijekoon
Faculty of Veterinary Medicine
Peradeniya, Sri Lanka
suranji@vet.pdn.ac.lk

Theekshana Dissanayake
Queensland University of Technology
Queensland, Australia
theekshanadis@eng.pdn.ac.lk

***Abstract*—Emotions are complex processes and humans communicate beyond words by expressing the emotions. They assess each other's emotions in an unconscious way. It becomes interesting to think about the possibility that machines can distinguish affective states and recognize one's emotions. Emotion recognition systems are an important technology that enables affective computing, which is a branch of computer science that combines human emotions with artificial intelligence into systems and devices. There are a lot of ways to build an emotion recognition system using various techniques and algorithms. This review paper analyzes scientific research and technical papers that adopted electrocardiography (ECG) and machine learning techniques as approaches for emotion recognition. A review of how the heart works, how electric signals are produced, and how those signals are captured as ECG is done. To perform emotion recognition, there should be an organized method of emotion classification and emotion modeling quantitatively. The two types of scientific emotional models are explained and reviewed here. Further, the available ECG-inclusive physiological databases in the literature are analyzed and summarized as well. Thorough and critical observations of emotion elicitation, emotion evaluation, data acquisition, signal pre-processing, feature extraction, feature selection and dimensionality reduction, classification, and validation are conducted. Additionally, this paper reviews and compares the existing architectures and models of ECG-based emotion recognition systems of both humans and animals available in the literature. The gaps in the area is presented based on the literature reviewed and future work is suggested and concluded.**

***Index Terms*—Emotions, affective computing, electrocardiography (ECG), emotion recognition system, physiologic sensors, affective dimensional model (ADM), physiological datasets, heart rate variability (HRV), machine learning,cross-validation**

I. Introduction

Beyond words, emotions are thought to be the best way to communicate. They are intricate processes involving feelings, body movement, and even cognitive reactions or thoughts. Humans communicate beyond words by analyzing key points such as facial expressions, speech intonation, and body language, and are made up of both verbal and nonverbal components capable of carrying emotional information. Every day, humans rely on their own interpretation of facial and speech tone to infer other people's emotional states. Recognizing people's emotional states is critical for understanding their behavior and making decisions. Affective computing is a developing field that combines engineering, psychology, cognitive science, and even sociology to investigate how technology can be used to recognize and interpret human emotions or affects. The field of computer science is constantly involved with the domain of emotion recognition because it has a large potential for applications in emerging technologies. This includes healthcare, entertainment, e-learning, marketing, human monitoring, and security.

Emotion is a psychological and physiological expression that is related to mood, personality, and all cognitive processes. These signals are continuously recorded, allowing for the detection of emotional variations over time. Since then, emotion recognition using physiological signals has grown in popularity because it can reveal the true state of emotions felt within the human body. Physiological signals are collected in a more unconscious manner, allowing for more reliable data collection. Because they are associated with autonomic nervous system responses, physiological signals should provide relevant insights into emotion. The experimental subjects are unable to easily alter any physiological signals, resulting in accurate dataset collection. Different physiological signals, such as electroencephalograms, galvanic skin response (GSR), electromyogram (EMG) have been used to detect emotions efficiently.

The autonomic nervous system (ANS) connects the brain and heart, allowing them to influence each other's behavior indirectly. The ANS includes the connection between the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). Thus, emotional experiences do cause changes in heart rhythm, which can be detected using ECG readings. The electrocardiogram (ECG) is a powerful signal, and recent studies have shown it to be a promising technique for emotion recognition, allowing for the measurement of signals that can be affected by changing emotional states. ECG as an input to emotion recognition systems is discussed here, as are ECG features such as heart rate (HR), heart rate variability (HRV), and their relationship to the heart.

Affective Dimensional Models (ADM) define an emotion as a set of parameters that form an n-dimensional emotional space, with the most commonly used dimensions being arousal, valence, and dominance. Arousal can be defined as an indicator of emotional stimulation. Valence is a measure of pleasure, while dominance is associated with the subject's sense of control. Fear, for example, has a high arousal level, a negative valence, and is a submissive emotion [53]. For affect recognition, pattern recognition approaches must be used, which rely on the acquisition of data with different affective states from subjects experiencing a given situation. This information was gathered using a variety of methods, including facial expressions, peripheral physiological signals, and even speech intonation. In terms of emotional stimuli, this can include media such as video, audio, or even music clips, as well as the creation of various environments. Various machine learning models and efficient mathematical models have also been proposed over the years in order to extract, classify, and analyze emotions. This paper discusses data collection, pre-processing, feature extraction, feature selection and dimensionality reduction, classification, and validation. Different architectures and ECG-inclusive affective databases are also examined. Thus this paper performs a review on emotion recognition using ECG and Machine learning techniques and further continues to discuss and compare the existing architectures and models of ECG-based emotion recognition systems of both the human and animal emotion recognition.

II. Electrocardiography

A. Anatomy of Heart

The human heart is the primary organ of the cardiovascular system, which is the network of blood vessels that circulates blood throughout the body. This muscular organ is vital to human life because it acts as a pump, contracting and forcing blood through the body's blood vessels. The network of nodes, cells, and signals that controls the heartbeat is known as the heart conduction system. The heart performs three major functions: (1) generating blood pressure, (2) routing blood, and (3) regulating blood supply, with both the heart rate and force contraction changing in response to the human metabolic needs [66]. Electrical signals travel through the heart every time it beats. These signals cause various parts of the heart to contract and expand. The expansion and contraction of the heart and body regulate blood flow. Throughout the contraction and expansion, the electrical impulse follows a specific order and route [55]. Electrocardiography is a technique for examining the heart's conduction system, which offers information about the heart's electrical activity. An electrocardiogram (ECG) is a physical representation of the conduction system monitoring. ECG, as a physiological signal, is used as the standard method for noninvasive interpretation of the electrical activity of the heart in real time [20]. Because heart activity is related to the human central system, ECG can be used not only for analyzing heart activity but also for emotion recognition [26].

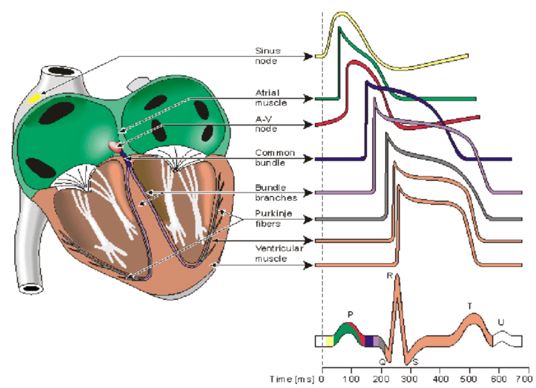

Fig. 1. Pathway of an electrical impulse throughout the heart as it corresponds to the spikes and waves on an ECG [35]

The heart muscle has a specific rhythm for pumping blood throughout the body. This requires the contraction of the heart muscle, which needs an electrical impulse. Electrical impulses originate in the Sinus Node and are responsible for heartbeat continuity. The electrical current is subsequently transferred through precise routes throughout the heart, allowing for regular contraction (depolarization) and relaxation (repolarization). Using adhesive electrodes, this electrical current can be sensed on the body's surface and shown as an ECG signal.

B. Electrocardiograph

The ECG signal is the physical representation of the electrical activity of the heart over time. It is a graph of voltage versus time. Recording ECG is a simple procedure. The electrodes are attached to the surface of the body and the ECG is recorded without any harm to the body [2]. The P waves, the QRS complex and the T waves are the main wave components of a typical ECG. Each wave is a result of the activity of the heart. P waves indicate depolarization of the atria. QRS complex indicates depolarisation of the ventricles and the simultaneous repolarization of the atria.T waves indicate ventricular repolarization.

The duration of atria contract and starts to relax is represented by the PQ or QR intervals, the duration between the beginning of the P wave and the QRS complex. The ventricles start to depolarize after the PQ interval. The duration for ventricular depolarization and repolarization is represented by the QT interval, the duration between the beginning of the QRS complex and the end of the T wave. In that time interval, the duration of ventricles is completely depolarised and the repolarization of ventricles is represented by the ST interval, the time between the end of the QRS complex and the start of the T wave [17].

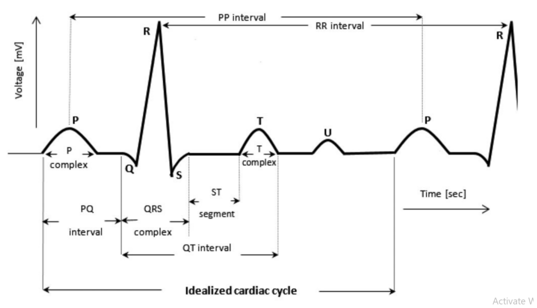

Fig. 2. ECG cycle in a healthy and normal heart [29].

There are many desirable properties of ECG. Universal, permanence, uniqueness, robustness to attacks, liveness detection, continuous authentication, and data minimisation are mentioned in the [2] as desirable characteristics of ECG biometric modality. Nevertheless, a number of studies have examined the use of ECG signals for emotion recognition as follows.

1) Certain emotional characteristics are influenced by the physiological interaction between heart and brain communication. Dynamic, continuous and bidirectional communication of both heart and brain influence perception, emotion, intuition, and overall health. Therefore, to recognize emotions, detecting cardiac rhythm is necessary [29].
2) According to Rattanyu [51], and Bexton et al. [7] the quality of ECG and carrying information about human emotions are reasons for ECG sensors becoming the most widely used biosensors in the emotion detection research area.
3) Theekshana et al. discuss four reasons for the ECG-based emotion recognition method to be an adequate solution. ECG signals capture the heart activity, and Autonomic Nervous System (ANS) stimulation toward each emotion causes rhythmic changes in the heart, ECG sensors can be used as wearable devices, an ECG is a versatile biosensor that can collect data from different parts of the body, ECG signals have a higher amplitude than other biosignals
4) In [17] Magalhaes et al mainly discuss seven reasons for visible differences in the ECG data. Heart Geometry, Physical Exercise and Meditation, Individual Characteristics, Cardiac Conditions, Position and Shape of the Organ, Emotions and Fatigue, Electrode characteristics and placement are the seven reasons. They further discuss the effect of emotion on the variability of the ECG depending on the subject as well as the emotional state.

Finally, [2] discusses challenges when large-scale deployments are envisioned. Time dependency, Collection periods Privacy implications, and Cardiac Conditions are those challenges.

III. Emotional Modeling

To perform emotion recognition, there should be an organized method of emotion classification where emotions should be able to be addressed quantitatively. In the literature on emotional intelligence, there are two common ways of modeling emotions. The first one is to divide emotions into discrete categories and the other is to define emotions using multiple continuous dimensions [50]. These scientific models are namely the Discrete Emotional Model(DEM) and Affective Dimensional Model (ADM).

A. Discrete Emotional Model

The Discrete Emotional Model(DEM) classifies emotions using common descriptors such as happiness, sadness, surprise, anger, disgust, and fear [64]. This discrete model claims that these states of emotions are standardized and universal among people from all cultures. The first documented emotion recognition using physiological signals by Ekman [21] presents six basic discrete and measurable emotion categories. Further Cicero and Graver [28] present four basic categories while Izard [30], [31] presents ten basic categories. All other emotions were considered to be combinations of these basic emotions.

B. Affective Dimensional Model

Russel [54] developed the first affective dimensional model of emotions, presenting that emotions can be described by some evaluation parameters, such as intensity and positiveness. This leads to the concept that emotions are continuous, not discrete. With the continuous model defining emotions, it can be described as the correlation among likely emotional states such as pleasure vs liking, and grief vs sadness [9]. Further, it can quantify and compare corresponding intensities of emotional states such as happy vs very happy.

The work of Lang [41] presents these continuous emotions that can be investigated in a two-dimensional model. The planes of the model are valence and arousal. Here valence is a measurement of pleasantness and ranges from unpleasant/negative to pleasant/positive. Arousal is the activation level of feeling and it ranges from passive/low to active/high [32]. Figure 3 shows the basic emotions plotted on the valence-arousal place. Mehrabian [44] extended the emotion model from a two-dimensional to a three-dimensional model. The third dimension axis is Dominance, which represents the authority to be in control. Figure 4 shows the emotion visualization on a 3D model.

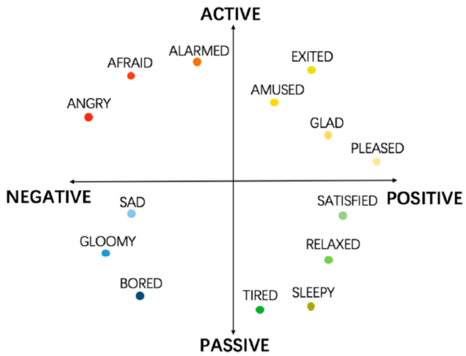

Fig. 3. Two-dimensional space emotional model [60]

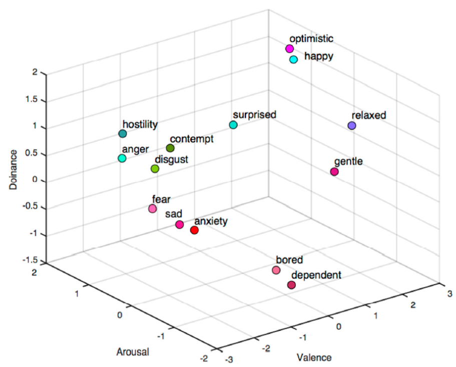

Fig. 4. Three-dimensional space emotional model [60]

IV. Datasets

Several datasets based on physiological signals, including ECG present in the literature. These datasets are widely cited for research based on emotion recognition using physiological signals. Here in this section, the focus is to summarize widely used publicly available ECG inclusive physiological datasets based on the number of subjects, number of electrodes, electrode placement, stimuli used and assessment method.Table II shows the summary of the datasets of AMIGOS [45],ASCERTAIN [65], DECAF [1], DREAMER [36], MAHNOB-HCI [63], SWELL-KW [58], WESAD [39].

a) AMIGOS: The purpose of creating this database was to create a database for personality research based on neurological and physiological signals. In this research, the 36 videos used in DECAF have been used. Videos have been categorized into four quadrants in table I. And three videos were selected for each quadrant. Moreover, four videos have been selected for each quadrant from videos used in MAHNOB-HCI. Selected subjects were between 21years old and 40 years old. The device used to collect data was a wearable sensor Shimmer 2R5 extended with an ECG module board. The placements of three electrodes are as follows, two of them on the right and left arm and the third in the internal part of the left ankle. Two experimental scenarios, individual settings and group settings have been considered. Both Internal

TABLE I
THE FOUR QUADRANTS USED IN AMIGOS

Quadrant	Vlance	Arousal
Quadrant 1	High	High
Quadrant 2	High	Low
Quadrant3	Low	High
Quadrant 4	Low	Low

annotation and external annotation were used to label the obtained samples [45].

b) ASCERTAIN: This is a multimodal database that is the first physiological database that facilitates both emotion and personal recognition. The same set of videos used in DECAF was adopted. 58 university students were selected for the subjects. Their mean age is 30 years old. The devices used to collect data are commercial physiological sensors. The sampling rate is 256 Hz. For the ECG measurements two electrodes were placed at each arm crook, and the reference electrode was positioned at the left foot. In this procedure self-assessment, and ADM was used to label data samples [65].

c) DECAF: This research aimed to present one of the largest multimodal emotional databases available to the affective computing community. 36 videos have been selected based on previous studies [5].The aim of Bartolini et al. [5] was to create an updated database which can use to elicit intense and discrete emotions more reliably. It contains short film clips. Labels are generated(emotion elicited by the video) using a more effective and reliable process described in the paper [1].The length of the videos was 51.1–128.2 sec long. Also, emotional responses to 40 one-minute music videos used in the DEAP study were recorded. Subjects engaged in the experiment were 30 university students, an age range of 27.3 ± 4.3 years. As the initial step of the experiment, four-second video clips were shown to ensure the subject is in his/her resting state. The ECG signal was recorded at a sampling rate of 1KHz, subsequently downsampled to 256Hz. Three electrodes were used and their placements were, two electrodes on the wrist and the reference on a bone part of the arm. Self-assessment valence-arousal ratings for music and movie clips provided by the participants were used to generate suitable labels for the collected data samples [1].

d) DREAMER: DREAMER is a multimodal database. It contains electroencephalogram (EEG) and electrocardiogram (ECG) signals recorded. Stimuli selected is a set of videos containing 18 film clips. The length of the film clips was between 65 to 393 s. Twenty-five volunteers aged between 22 and 33 years old was the selected subject. A SHIMMERTM wireless sensor at 256 Hz was used to record ECG measurements. It can produce RA→LL and LA→LL vectors, only the RA→LL vector was used. The experiment procedure started by showing a neutral stimulus. A self-assessment procedure was followed to obtain data about felt emotions by reporting felt arousal, valance, and dominance on a five-point scale. Further, the coefficient of variation was applied to the data obtained through self-assessment to identify any variations in the self-assessment [36].

TABLE II
SUMMARY OF THE COMMONLY USED ECG DATASETS FOR EMOTION RECOGNITION

Database Name	No.of Subjects	No. of Electrodes	Electrode Placement	Stimuli
AMIGOS	40	3	Arms, Left Ankle	16 short emotional videos 4 long videos
ASCERTAIN	58	3	Arms, Left Foot	18 affective videos and 90-minute sessions
DECAF	30	3	Wrists, Arm (boney part)	40 1-minute music records and 36 movie clips
DREAMER	23	3	Lead I and Lead II vector	18 affective videos
MAHNOB-HCI	27	3	Chest	20 emotional videos and Image Tagging
WESAD	15	3	Chest	neutral, amusement, stress: TSST
SWELL	25	3	Chest	neutral, stressor time pressure, stressor interruptions

e) MAHNOB-HCI: MAHNOB-HCI is also a multimodal database. The aim of creating this is to record responses to affective stimuli with the goal of emotion recognition and implicit tagging research. Implicit affective tagging will automatically understand an individual's response to media items. Twenty video clips containing movie scenes were selected, which were 34.9 -117 seconds long. Selected subjects were from 19 years old to 40 years old. A shorter neutral clip showed to the subject before each emotional video. The device used was a Biosemi Active II. The sampling rate was 1024 Hz. Electrode placement was two of the electrodes on the right and left corners of the chest, below the clavicle bone and the third electrode on the abdomen, below the last rib. Emotional responses to videos and implicit tagging are the two experiments that were carried out. A self-assessment form used to obtain the affective state of subjects with ADM (Affective Dimensional Model) [63].

f) SWELL-KW: SWELL knowledge work is a multi-modal dataset created for stress and user modelling research purposes. Stimuli for this experiment were knowledge works like report writing and making a presentation on pre-defined topics. Participants were knowledge workers. Their average age was 25 years. The data was collected using a Mobi device(TSMI) with a self-adhesive electrode at a 2048Hz sample rate. One electrode below the right collarbone and the other below the chest, with the grounding electrode below the left collarbone, is the electrode placement used to measure ECG. The self-assessment method is used to obtain the effective state of subjects. Participants rated valance, arousal, and dominance they felt from 1 (low) to 9(high) [58].

g) WESAD: Another multi-modal dataset. It features physiological and motion data recorded during a lab study. Neutral reading material (magazines), a set of eleven funny video clips, a guided meditation, and a well-studied Trier Social Stress Test (TSST) consisting of public speaking and a mental arithmetic task were used to elicit emotions. The mean age of the selected 15 subjects was 27.5 ± 2.4 years. Chest and wrist-wearing devices were used to collect physiological data at a 700Hz sampling rate. A self-assessment questionnaire was carried out to obtain data about felt emotions [39].

All the above datasets are multimodal datasets containing ECG data as well. The self-assessment method is used with different changes to evaluate the felt emotions. The Affective Dimensional Modal has been considered frequently in the above datasets. In most cases, only three electrodes are used to obtain ECG measurements but with different placements. In some experiments, one fact considered when selecting a stimulus is as follows. According to psychologists, to elicit a single emotional video between 1 to 10 mins is sufficient. Since the emotional state of a person tends to change over time, using a lengthy stimulus may cause unreliability [36]. Table II summary shows that most of the datasets have used a lesser number of subjects and experiments per subject. Therefore, none of these datasets is extremely large. Also, in most experiments, only the subject's evaluations were considered for labelling the collected data samples. Due to these constraints, it may encounter troublesome limitations. Unreliability and uncertainty in the labelling is one drawback [39]. Moreover, using the same dataset when reproducing a given method is an important factor [17]. However, deep learning methods require large amounts of data samples.

V. METHODOLOGY

The ECG usage in emotion recognition systems is quite recent but shows popular usage. Thus literature shows some common methodologies adapted in the usage of ECG for emotion recognition having well-known steps. The specific methodology for identifying emotions from ECG data can be separated into two main categories: (1) Feature-dependent machine learning approaches (i.e: traditional machine learning techniques), and (2) Feature-independent machine learning approaches (i.e: deep learning techniques) [17]. The difference between the two methods is the feature-dependent machine learning approach requires a handcrafted feature engineering process whereas the feature-independent approaches learn from the unaltered data. Figure 05 shows the mentioned methodologies for automated emotion recognition systems. This review paper specifically focuses on the automation of emotion recognition using the first approach: the traditional machine learning approach.

As the literature shows, the most common well-established steps for ECG emotion recognition systems using traditional machine learning are (1) Emotion elicitation, (2) Data Acquisition, (3) Emotion evaluation, (4) Signal preprocessing, (5) feature engineering, (6) Emotion Classification and (7) Validation [9], [17], [29].

The first step: Emotion elicitation is to induce targeted emotions inside the subject. Next, the data acquisition step records the ECG data. Emotion elicitation and Data acquisition actions are synchronous because the recording of ECG data should happen while the subject is experiencing the targeted emotion. The third step: Emotion evaluation is to annotate or label the subject's emotion on the data collected. Next step: Signal pre-processing which is to clean the collected data from the noises. The fifth step: Feature engineering contains a few sub-steps: feature extraction, feature selection, and dimensionality reduction. The last two steps: Classification and Validation are the steps where machine learning techniques are used. Figure 5 shows the general pipeline for ECG-based emotion recognition systems.

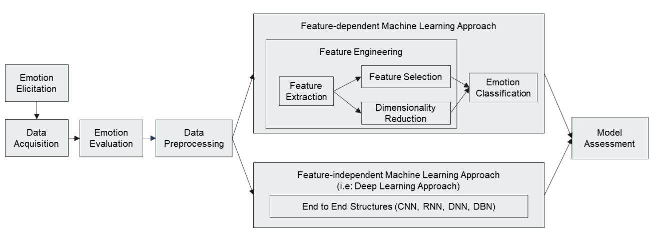

Fig. 5. General pipeline for ECG-based emotion recognition systems

When it comes to the usage of the developed emotion recognition system Figure 6 shows the procedure. As the development procedure data acquisition has been done while emotion elicitation and follows the signal pre-processing, feature engineering, and feeds the extracted features to the developed classifier. By following this usage procedure system predicts the emotion experienced.

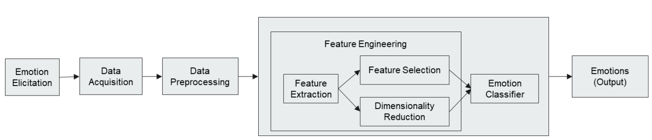

Fig. 6. General pipeline for ECG-based emotion recognition usage procedure

The following sub-sections describe more about emotion elicitation, emotion evaluation, data acquisition, data pre-processing, feature engineering, classification, and validation.

A. *Emotion Elicitation*

In an emotion experiment triggering basic emotions within the subject has to be done to gather the data sets. This process of inducing basic emotions is defined as emotion elicitation. This has to follow a standard and pre-validated operating procedure because emotion elicitation has high variability subjectivity. There are some common emotion elicitations techniques presented in the literature which are audio-visual, imagery, music, autobiographical recall, and situational procedure [61]. Some of the less common techniques that can be found are video games, and naturalistic conversations, virtual reality.

Audio-visuals: This technique uses film clips or videos to induce the targeted emotions. The length of the recorded signal is the length of the video [38], [64]. The work [23] presents a validated catalog of film clips for emotion elicitation with 295 film clips from 24 articles. Furthermore, the LIRIS-ACCEDE database [6] is developed using 9800 video clips from 160 movies and sorted along the valence-arousal scale. The experiment [61] describes that audio-visuals are the most effective technique to trigger all basic emotions: Happiness, sadness, fear, disgust, surprise, and anger.

Imagery: This technique involves reading vignettes and experiencing emotions by contemplation [43], [61]. Furthermore, the usage of graphical pictures for emotion elicitation is widely present in the literature. The International Affective Picture System (IAPS) [42] contains a wide range of photograph collections for emotion elicitation of pleasure, arousal, and dominance. Furthermore, Geneva Affective Picture Database (GAPED) [16] contains images of positive, negative, and neutral content. Additionally, the Museum of Modern and Contemporary Art of Trento and Rovereto (MART) contains abstract artwork images annotated according to the positive and negative experiences [57]. The experiment [61] describes that imagery is only effective to trigger emotions: Happiness, fear, surprise, and anger.

Music: The technique of listening to music is another common method of emotion elicitation present in the literature. Music activates some emotions through lyrics, melody, and tempo [40]. Datasets like the International Affective Digitized Sound system (IADS) [11] contain audio stimulations covering categories of pleasure, dominance, and arousal which have been used popularly. The experiment [61] describes that music is only effective to trigger emotions: Happiness, sadness, and fear.

Autobiographical recall: This is the technique of recalling personal emotional experiences or memories to bring back the original emotion that was present at the time. The experiment [61] describes that autobiographical recall is only effective to trigger emotions: happiness, anger, disgust, sadness, and fear, but not surprise.

Situational procedure: This technique involves creating a social context that generates the desired emotion. The experiment [61] describes that situational procedure is only effective to trigger emotions: Happiness, anger, fear, and surprise.

To sum up, the use of audio-visuals is the most popular and effective emotion elicitation material that is present in the emotion recognition literature. Other emotion elicitation techniques also show some advantages as well as disadvantages. The imagery method is low-cost, user-friendly, and easy to conduct in laboratory settings. But it has the constraint of not being able to induce long-lasting emotions. The technique of music is also a low-cost and easily executable elicitation method. But this is biased by the music preferences and taste of the subject. Thus, the use of audio-visuals can be presented as a more reliable emotion elicitation method used by researchers.

B. Data Acquisition

The ECG signal has a wide range of applications, including medical diagnostics, biometric recognition, and emotion recognition as well. These goals are very different and necessarily require different experiments and requirements. In this way, they differ in the most commonly used ECG measurement and collection techniques.The signal quality of the ECG is affected by the acquisition techniques as well as general details like the type, size, and number of electrodes as well as where they are placed on the chest and limbs. The perspective and overall view of the electrocardiographic signal can be changed by electrode mispositioning. The most common ECG acquisition methods are presented in this section, first for medical diagnostic purposes and then for emotion recognition tasks.

Medical Diagnostic Acquisition Settings

There are some previously defined electrode configurations for medical diagnostic purposes that allow for standardized techniques to be applied, ensuring effectiveness and collection quality as well as comparable and reproducible results. The standard 12-lead configuration and the corrected orthogonal ECG configuration are the two most common methods.

Emotion Recognition Acquisition Settings

Only signals analogous to bipolar limb leads are normally used for ECG acquisition for emotion recognition experiments, indicating a less complex collection than medical standard acquisitions. This lead selection could be due to the fact that limb leads are generally more comfortable for the user.

Three sensors were attached to the participant in this paper [1]. Two electrodes on the wrist and a reference in the ulna bone (in the arm), which served as a ground electrode. This type of setup enables accurate measurement of heart rate (HR) and, as a result, heart rate variability (HRV), which is widely used and correlated with emotional states.

In this paper [36] ECG is recorded with a SHIMMERTM [13], a wireless sensor capable of obtaining Lead II and Lead III vectors, though they only used Lead II for further development. The ECG was recorded using a SHIMMER 2R and three electrodes in [45]. Two were placed on the right and left arm, and the third was placed on the ankle as a reference. This configuration allowed for precise identification of HR and the entire QRS complex. In [19] a Spiker-Shield Heart and Brain sensor, which has an inbuilt noise sensor was used along with two electrodes placed on the right and left arm. The comfort of the subject is ensured since they only need to have a few plasters on their hand in order to record the ECG signals. In other cases, rather than placing electrodes on the wrists or arms, some experiments place them below the collarbone [39], [63].

Thus, traditional emotion recognition experiments employ simpler and less complex ECG measurement techniques than those employed in the field of medical diagnostics. Wireless sensors, as well as fewer electrodes, are widely used, allowing for a more comfortable and relaxed setup for the subjects, who can move more freely.

C. Emotion Evaluation

The annotation process of the subjects' gathered emotional data is considered the emotion evaluation step. There are two methods of emotion evaluation present in the literature: internal evaluation and external evaluation.

Internal evaluation is often known as self-assessment or the first-person perspective evaluation. This is the most common way of emotion evaluation discussed in the literature. Self-assessment involves the subject evaluating their own affective emotional state and often experiments have been conducted using a questionnaire with a graphical description of emotions [10]. One of the drawbacks of the internal evaluation is it might make the subject uncomfortable disclosing their real conscious and unconscious reactions to the stimuli.

External evaluation is the process of assessing the subject's state by an external subject. Second-person perspective and third-person perspective are the methods involved in this technique. In the second-person perspective method, an external person performs real-time emotion labeling by thinking about what the subject feels towards the stimuli. In the third-person perspective method, emotion labeling performs after examining the recording of the subject's behaviors, facial expressions, and reactions. Both these external evaluation methods are often biased by culture, personality, and environmental factors.

D. Signal Preprocessing

ECG signal is a highly sensitive physiological signal and commonly the raw ECG data signals contain noise frequencies due to various reasons. Mainly ECG noise is raised due to power line interference, muscle movements, the electrode–skin contact, motion artifacts, baseline wander, electronic and electromagnetic device interference, external electrical system interference, internal high-frequency noise, and respiration or bowel sounds [29]. According to the literature, the Butterworth filter with several configurations is the most used filter to reduce noise. The work [19] has used a three-step procedure for pre-processing: filtering, detrending, and smoothing. With the last two steps, the filtered signal was stabilized and further smoothed using a Gaussian Kernel. In the pre-processing, it is important to be careful to maintain essential information of the ECG wave.

E. Feature Engineering

During the development of a classical ML system, a feature engineering step is implemented after the signal has been pre-processed. The major goal of this phase is to boost the ECG signal data's informative content. Following feature engineering, the output is introduced into a classifier with the emotion class label. Literature reports a few basic processes performed during feature engineering: feature extraction, feature selection, and dimensionality reduction.

1) Feature Extraction: It is possible to extract informative metrics soon after the raw ECG signal data has been preprocessed. These metrics which describe the physiological signals are denoted as features. These features allow the comparison between different signals and enhance the informative contents of the signal data. Based on the domain that these ECG signal features are extracting, they are categorized into two main categories: Time domain features and Frequency domain features. Furthermore, features are also can be categorized as fiducial features and non-fiducial features. Fiducial features are referred to as the features that are extracted using specific points and markers of the ECG signal such as PQRST wave location data, their interval statistics, time, and amplitude. In contrast, non-fiducial features are referred to as the features extracted by taking into account the signal as a whole, or portions of it.

Time Domain Analysis: As section 4.1 discussed, the ECG signal describes the variation of the electrical activity of the heart over time. Furthermore, the ECG signal wave is mainly constructed with a P wave, a QRS complex, and a T wave. Different heart activities are represented by each of these signal segments. However, Heart Rate (HR) and Heart Rate Variability (HRV) are the main visible changes noticed on the ECG signal which are correlated to emotions. Hence, heart rate variability-related parameters are the most considered in the time domain feature analysis. Heart rate [46], R-R intervals and R peak value [48], the standard deviation of NN intervals (SDNN) [37], and root mean square for standard deviation (RMSSD) [24] are major time domain emotion-related features discussed in the literature.

Frequency Domain Analysis: The ECG signals have to be transformed into the frequency domain from the natural time domain to extract the frequency domain-related features. Fast Fourier Transforms (FFT), ContinuousWavelet Transform (CWT), DiscreteWavelet Transform (DWT), the Hilbert transform, and the Power Spectral Density (PSD) are some of the most mentioned frequency domain feature extraction techniques discussed in the literature [17]. Most of these features in the frequency domain are non-fiducial.

Fiducial Features: These are the features associated with specific points and markers. The PQRST points of the wave are the most fundamental markers to be extracted from the ECG signal. The interval between two successive QRS complexes can be used to determine the heart rate. In literature, the QRS complex is the most used time-domain, fiducial feature for emotion recognition activities [17]. Furthermore, using the PQRST location information, some more statistical features can be derived [36], [69]. The mean, median (med), standard deviation (std) and quartile deviation, minimum(min), maximum(max), and range (max-min) of individual P, Q, R, S, and T are among the statistical features extracted.

Non-fudicial Features: As mentioned non-fiducial features are referred to as the features extracted by taking into account the total signal or segments of the signal. This approach offers the ability to use a variety of techniques in the time and as well as frequency domain because it is not restricted to certain fiducial points. Empirical Mode Decomposition (EMD) and Bidimensional Empirical Mode Decomposition (BEMD) can be given as common specific methods to obtain time-domain features. The work [3] by Agrafioti et al has used EMD-based feature extraction. Both time and frequency domain features were extracted in the work [25].

2) Feature Selection and Dimensionality Reduction: The features extracted during the feature extraction step may not guarantee a complete relevant correlation with the physiological adjustments in the emotion variations. This can optimize the classification architecture by excluding non-informative features and selecting only the best feature combinations. As a result, it reduces computational costs and increases classification accuracies [27]. In the dimensionality reduction step, the number of features is reduced by transforming a higher dimensional feature matrix into a lower dimensional matrix without missing any important data. Linear Discriminant Analysis (LDA) and Principal component analysis (PCA) are some of the most commonly discussed techniques of feature selection and dimensionality reduction in the literature. The use of the aforementioned, feature selection and dimensionality reduction approaches improves the training and testing precision of emotion recognition systems because it takes much less time and fewer data to be processed at once in the classification step.

F. Classification

A classifier is required after the feature extraction to perform a proper emotion classification. One of the major important aspects of the emotion classification step is deciding the number of classes and the type of classes of the classifier. The models are developed from a data set mapping ECG signal features to their label classes. In the literature, there are two common methods of adapting labels in emotion recognition systems: (1) Discrete Emotion Classes and (2) Dimensional Emotion Classes. In discrete emotion class methods, the emotion labels are adopted from emotion models: commonly the Discrete Emotion Model (DEM). This is result in predicting specific emotions such as happiness, joy, sadness, and anger. In contrast, the dimensional emotion class classification methods predict parametric classes such as valence, arousal, and dominance.

According to the literature, some of the most commonly used machine learning classifiers for ECG-based emotion recognition systems are Support Vector Machine (SVM), Naive-Bayes(NB), k-Nearest Neighbour(K-NN), and Linear Discriminant Analysis (LDA), etc. The SVM classifier is the most commonly used in the literature [9]. Classifiers such as decision tree(DT), random forest(RF), AdaBoost(AB), gradient boost(GB) are also reviewed in the literature. When compared to RF and GB, the performance of less well-known classifiers such as an additional tree, regression tree, and ensemble bag tree was said to be noticeably better in [19].

G. Validation

After the development of the trained machine learning model, the final step of a machine learning approach is the validation of the model. This is an important step especially for emotion recognition because it is a subjective application. In this step, the model should perform on new data which is as in real-world scenarios outside the experimental setup [9]. This process allows the model to reduce overfitting and increase variability. Cross-validation (CV) with different versions has been widely used as a validation technique. Those techniques can be categorized as shown in the figure 7.

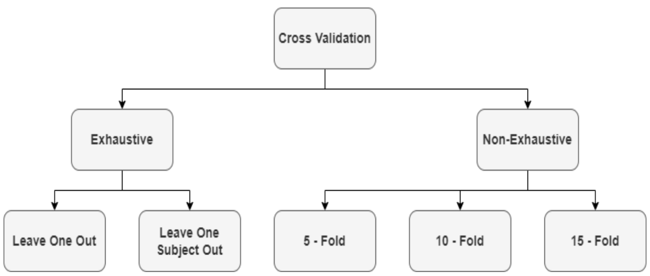

Fig. 7. Categorization of different cross-validation techniques used in literature.

In the literature the cross-validation techniques used are Leave One Out, Leave One Subject Out, and K-Fold(where K= 5, 10, and 15). Leave-one-out cross-validation (LOOCV): If the training set contains N data, LOOCV trains the machine learning model using N-1 data and tests it with the remaining one datum to evaluate the classification error. K-fold cross-validation (KCV): The training data will be divided into K segments. Then each segment is cross-validated individually. This technique involves a smaller computational load. Leave-one-subject-out cross-validation (LOSOCV): Similar to KCV. But this technique divides the entire data into datasets for each of the subjects for cross-validation [14].

According to Hasnul, M.A et al [29], the widely used exhaustive validation method is Leave One Out cross-validation(LOOCV). The 10 - fold cross-validation is the non-exhaustive cross-validation method most commonly used. However, when physiological data are analyzed verifying the performance of the trained classifier through leave-one-subject-out cross-validation (LOSOCV) is recommended [14].

VI. Review on Emotion Recognition Systems

A. Human Emotion Recognition

The reviewed works are summarized in Table III and it contains unimodal ECG-based affective research that are available in the literature.

Data were labeled using a DEM with four classes of emotions—happy, sad, pleasant, and angry—in a study by Zhang et al. [71]. The ECG unimodal approach was reported to have a 92% overall accuracy rate. The respective accuracy rates for angry, sad, happy, and pleasant were 97%, 92%, 91%, and 88%. KNN was used to combine the output of two sets of extracted features to produce the best classification results out of three classifiers. The time and frequency domains, along with statistical characteristics of ECG signals, made up the first feature set. Correlation features made up the second feature set. The cross-correlation feature, multifractal feature, and autocorrelation feature parameters were all included in the correlation features. The max-min ant system was used to choose the features.

First, a self-supervised emotion recognition study was carried out by Sarkar and Etemad [56] using the AMIGOS, DREAMER, WESAD, and SWELL datasets. The neural network learned high-level abstract representations from the raw ECG signals in each dataset, and the weight was then transferred to an emotion recognition network. When compared to fully supervised learning, the results indicate improved performance. WESAD and SWELL were allegedly successfully classified, with accuracy above 90%, while AMIGOS and DREAMER failed to pass 90% and above accuracy. The Pos/Neg Model was successfully used by the author to classify WESAD with a 96.9% accuracy rate. Furthermore, the author was able to categorize SWELL using a model based on a binary scale of valence, arousal, and stress with 97.3%, 96.7%, and 93.3%.

B. Animal Emotion Recognition

As mentioned in [47], examining animal feelings has various benefits. One is, that it allows us to get more knowledge about our own emotions because humans are also animals. Also, that paper discusses the importance of studying the emotions of farm animals. One of the discussed importance is it helps us to be better owners of animals. Moreover, to evaluate the quality of animal farms need to have a better understanding of the emotions of animals. Because the productivity of the animals proportionally equals their happy emotions [47]. Animals react to changes in the ecosystem. So we can gather knowledge about the changes in the ecosystem through the emotions of animals. The research paper [62] discusses four importance of detecting animal emotions. Predicting the pain level intensity, animal protection, Communication is easier and security are those important. Neethirajan et al. [49] mention that primates and birds can experience emotions similar to humans' understanding of emotions. also, Singh et al [62] mention that understanding the emotions of primates is easier than understanding emotions in other creatures because the gestures of primates are more similar to human beings. The main difference between human and animal emotions is humans have mixed emotions while animals have simple and basic emotions. Even though animal emotions are simple, we need to have a proper scientific program to identify them. Moreover, De Waal et al. [18] mention that we can presume that humans and other related species of animals have more alike emotions if their responses are similar under the same conditions instead of supposing the animal emotions are basic and simple. Also, they conclude that humans and primates do not have a significant contrast in the way they feel emotions [18].

In the literature, some researchers discuss issues in animal (non-human) emotion recognition. Animals cannot express emotions as humans. Some animals use vocalizations such as growls, murmurs, barks, roosting calls, or purrs while Other animals use tails and body posture to convey their emotions [47]. However, those signals may not reliable. According to Neethirajan et al. [47] major issue in identifying signals related to emotions of animals is most of the related studies are not done on free range or wild animals. Instead, have researched domesticated animals or captivated animals. The research was done by K. Ohno et al. [49] using SAR (Search and Rescue) dogs is an example. That research emphasizes that the method used to collect data from SAR dogs cannot use for general dogs.

Table IV shows a summary of animal emotion detection models in the literature. It summarizes devices used in the experiment, the method used to detect emotion, the type of animal used for the experiment, detected emotions, the algorithms used to train the model, and the accuracy of the trained model. In most research behavioural outcomes of the emotions like waging of the tail, and different positions are used to detect the emotion [4], [15], [22]. Machine learning algorithms like RF, SVM, KNN, LR, Nive Bayes, and Decision trees [4], [22], [49] as well as deep learning algorithms like ANN, VVG16 Convolution, and Neural Network [4], [15], [22] are used to train emotion detection models. When comparing the accuracies of models, the models that identify only Positive, Negative, and Neutral emotions have higher accuracies. The models that recognize emotions like happiness, anger, fear, relaxation, annoyance, curiosity, and alarm have lower accuracies than other models.

VII. Conclusion

Emotion recognition-related research shows tremendous growth and it shows many published papers in the academic literature. This review has an overview of emotion recognition mainly using ECG and Machine Learning techniques. This paper begins by introducing important theoretical knowledge related to the heart work process related to emotions, how electric signals are produced, and how those signals are captured as ECG. Furthermore, this paper has reviewed the different emotional representation models, available ECG-inclusive physiological databases, and a comprehensive methodology of emotion recognition. Additionally, this paper reviews the existing ECG-ML works of emotion recognition systems of both humans and animals available in the literature. The major research gaps that were found through this review are a lack of affective databases with a large number of samples, less number of emotions predicted, and difficulty to study and analyze animal emotions. To conclude, future research on emotion recognition should address developing physiological emotion databases with more variety of subject ranges, and more research should be conducted to evaluate more emotions with better performances. Furthermore, a more reliable process of conducting animal emotion recognition research can add more value to the academic literature.

TABLE III
SUMMARY OF HUMAN EMOTION DETECTION MODELS IN THE LITERATURE

Source	Dataset	Adopted Emotion	Emotion Elicitation Method	No.of Sub-ject	Classifier	Validation	Accuracy
[3]	Own	ADM (valence, active/passive arousal)	Images (5)	44	LDA	NA	up to 89%
[52]	Own	DEM (anger, fear, sadness, disgust, joy, neutral)	Video	12	LDA, Adaptable KNN	NA	feature approach 37.23%, 3-feature approach 61.44%
[19]	Own	DEM (anger, sadness, joy, pleasure)	Video	25	RF, Extra Tree, Gradient Boost, AB SVM, AB DT, AB Naïve Bayes	10-fold CV	80% extra tree classifier and feature selection 79.23% RF classifier and extra tree feature selection 72.66% gradient boost classifier and RF FS
[8]	Own	Positive Negative Neutral	Video (15)	5	KNN, SVM	10-fold CV	”Pos/Neg Neutral KNN: 66.49% 60:40 train/test, 66.22% 70:30 train/test, 67.54% 80:20 train/test Pos/Neg KNN: 74.67% 60:40 train/test, 77.69% 70:30 train/test, 77.42% 80:20 train/test Pos/Neg SVM: 64.98% 60:40 train/test, 65.52% 70:30 train/test, 66.04% 80:20 train/test”
[59]	Own	DEM (happiness, sadness, fear, surprise, disgust, anger)	Video	60	Bayesian classifier, Regression tree, KNN, Fuzzy KNN	Random validation Subject-independent validation	Fuzzy KNN 6 Class: 92.87% RRS, 76.45% FVS
[67]	Own	DEM (joy, anger, sadness)	NA	8	KNN	10-fold CV	LBP: 84.17%, LTP 87.92%
[70]	Own	ADM (valence, arousal)	NA	16	SVM	5-fold CV	ADM: 72.9%, 89.6%V, 82.3% A
[33]	Own	Own DEM (happiness, sadness, fear, surprise, disgust, neutral))	Video(60)	30	LDA, KNN	NA	KNN: 52%
[34]	Own	DEM (joy, sadness)	Video(10)	391	KNN, Fisher-KNN	Run 9 times	KNN: 75.85%, Fisher-KNN: 85.78%V
[71]	Own	DEM (happy, sad, pleasant, angry)	Video	20	KNN, SVM, DT	CV	Best Classifier: KNN 4 Class : 92%, Happy: 91%, Sad: 92%, Pleasant: 88%, Angry: 97%
[68]	Own	DEM (sadness, anger, happiness, relaxation) ADM (valence, arousal)	Images (110)	30	SVM	LOOCV	4 Class: 79.29%, V/A: 79.15%, 83.55%
[56]	AMIGOS, DREAMER, WESAD, SWELL	-	Video, Audio	-	Self-Supervised CNN	10-fold CV	AMIGOS: 87.5% V, 88.9% A; DREAMER: 85.0% V, 85.9% A WESAD: 96.9% Pos/Neg; SWELL: 97.3% V, 96.7% A, 93.3% Stress
[12]	Own	DEM (fear, disgust, neutral)	Video	25	1-NN	Leave-one-out strategy	Fear: 77%, Disgust: 63%V, Neutral: 74% A

TABLE IV

SUMMARY OF ANIMAL EMOTION DETECTION MODELS IN THE LITERATURE

Reference	**Device**	**Emotion Detection Method**	**Animal**	**Detected Emotions**	**Model Training Algorithm**	**Accuracy**
[49]	Soft disposable electrodes to the M-X lead layout	Using ECG	Search And Rescue Dogs	Positive, Negative	Random forest	97%
[4]	A tail wearable device	Right, left and straight waging of the tail.which determine positive, negative and neutral emotions,respectively.	Dogs	Positive, Negative, Neutral	ANN	96%
					Random Forest	92%
					SVM	84%
					KNN	86%
					Nive Bayes	88%
[15]	-	Pictures, indicating emotional affect through the head, neck, ear,muzzle, and eye position	Horses	Alarmed, Annoyed, Curious, Relaxed	VGG16 Convolutional	65%
[22]	-	full body dog pictures containing different positions	Dogs	Anger, Fear, Happiness, Relaxation	Neural Net	67.5%
					Decision Tree	62.5%
					Logistic Regression	62.5%
					SVM	67.5%

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