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Advances in Non-Invasive Emotion Recognition: A Review of ECG and Radar-Based Emotion Classifier Systems

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Abstract

Emotion recognition has emerged as a critical area in human-computer interaction, mental health monitoring, and personalized healthcare. Many of the emotion classifier systems utilizes multimodal systems, lesser number of dingle modal systems are available in literature but with EEG signals. The acquisition of EEG signal is cumbersome but ECG signal acquisition is easier in comparison. Even with usage of mechanical movement of chest due to heartbeat can be translated into reconstruction of ECG signals, hence wireless acquisition of ECG is quite easier and employing single modal systems to come up with emotion classifier systems will be a promising field in integration of human emotion touch to modern AI based robotic systems. This review synthesizes recent developments focusing on electrocardiogram (ECG) signals and radar technologies for detecting emotional states through physiological responses. Key challenges, including signal noise reduction, accuracy in real-time scenarios, and multimodal fusion, are discussed. The analysis draws trends toward non-invasive, real-time systems with improved classification performance. The study also discusses current challenges and provides future directions for research.

Keywords

Human Emotion Recognition, ECG, Radar based systems, contactless detection, Machine Learning, Deep Network

I. Introduction

Emotion recognition has become crucial with the advancement in Human Machine Interaction (HMI) systems. It enables machines to comprehend the emotional state of the person resulting in natural interactions. This amalgamation of machine and human emotions has applications in various fields including, education, healthcare, security, market etc. Inclusion of emotion recognition in the machines not only provides better gaming experience, virtual assistance, tracking mental health of students, employees, labors etc., early detection of anxiety and depression for timely intervention but is also very essential for monitoring fatigue, frustration or distraction of drivers to prevent accidents and for lie detection, criminal interrogation, and monitoring of crowd. Various traditionally used systems for human emotion recognition utilizes recognition of facial expressions [1], speech [2], text [3], physiological signals (EEG, ECG, EMG, GSR), body posture [4] and gesture [5] etc. These systems have certain limitations associated with them. The facial expression-based systems are sensitive to light and speech-based systems are ineffective in the presence of background noise. These systems often utilize camera and microphones to record the image, video and audio data which can make the user uncomfortable and requires on body sensors for classification parameters which in itself a cumbersome process and hinders the daily activity of the subject. It can also present the false result if the human interacting with the machine mask the emotions. The system is less reliable for expressions depends on the persons age, culture, personality, habit and nature.

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Radar systems, such as frequency-modulated continuous wave (FMCW) and Doppler radars, offer noncontact monitoring of emotions facilitating acquisition of classification parameters non-invasively from a distance that enables human emotion recognition in the natural environment. Unlike the traditional systems which require proper lighting, noiseless environment, the radar-based system utilizes the electromagnetic waves to sense even the minute variation in physiological signals which are associated with the emotions [6] [7]. Xiaochao Dang et al. has reported a millimeter wave radar for non-contact detection to record heartbeat and respiration signal. He has proposed a deep learning model combined with CNN and Bi-LSTM for the classification of four different emotions [7]. In [8] researchers have recorded the chest movement of 35 people showing them emotional videos to trigger emotions like happiness, fear, and disgust. The breathing rate of all the subjects are estimated from the radar data and the results were compared with pulse oximeter. The results displayed 76% accuracy. Yuan Li et al. has utilized ultrawideband (UWB) radar to acquire the physiological signals of the human subject and Convolutional Vision Transformer (CVT) model for analyzing the radar signals. The accuracy achieved by this technique is 86.25% [9].

A typical radar-based system is shown in Fig. 1 which consist of a Radar sensing module which transmit the electromagnetic signal and receives the bounced back signal from the chest of the human subject. The acquired signal is then converted to digital signals using ADC. In the next step the signal is enhanced by removing the noises and unwanted signals. Furthermore, the features are extracted from the physiological signal to make it interpretable. Afterward the most suitable machine learning or deep learning algorithms are utilized to map the features to the respective emotional states in order to label the emotions. Then the recognized emotional state is presented in the form of output.

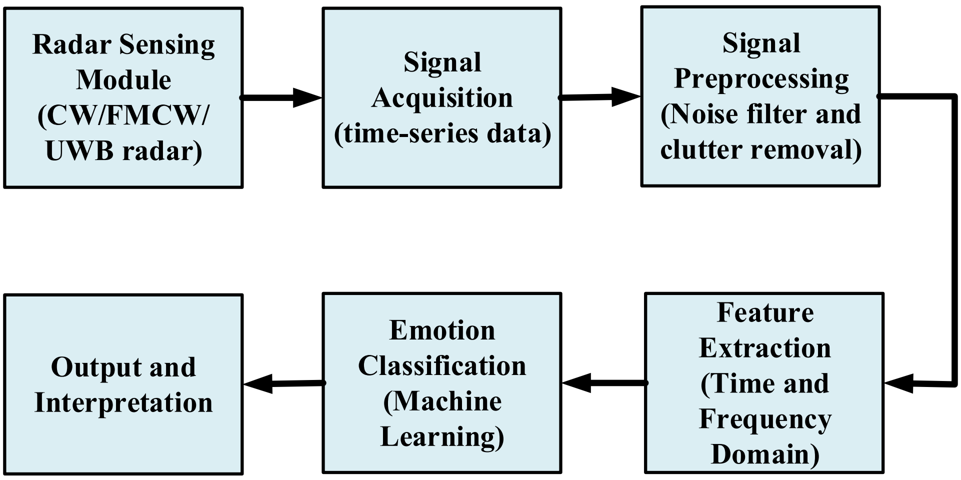

Fig. 1. Functional Block diagram of a typical radar based human emotion recognition system

This review illustrates the technical trends in ECG based human emotion classification system using radar-based technology. In Methodology section, various radar-based techniques with category of signal processing techniques, and emotion classifier systems are explained in concise manner. Furthermore, next section-III comprises of physiological signals having potential to be utilized in feature extraction and selection to devise a highly accurate and sensitive emotion classification systems. Section IV lists out the type of classifier models and performance metrics in the field of emotion classification. At last, section V and VI highlights the future trends & recommendations and conclusion respectively.

II. Methodology

The RADAR technology utilizes the radio and microwave signals to monitor, track and detect a human subject. The signal in radio micro frequency range are targeted on the chest of the subject and the reflected signals are analyzed for the emotion recognition application. Various types of RADAR system

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have been very effective in acquiring the ECG data. The block diagram representing architecture of radar based human emotion recognition system is shown is Fig. 2.

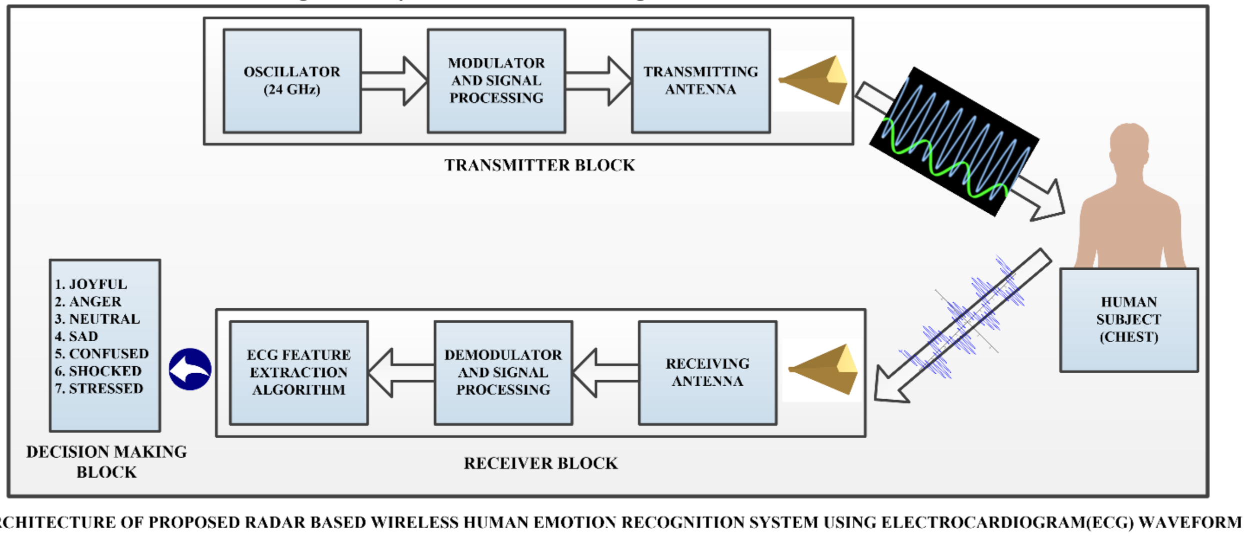

Fig 2. Architecture of radar based wireless human emotion recognition system using electrocardiogram (ECG) waveform

A. Continuous Wave (CW) Radar

Continuous wave radar is a type of radar system which transmits unmodulated continuous signal towards the target. The reflected wave with the frequency shift is received continuously which is used to measure the motion using dopplers effect. This radar system is capable of acquiring the minute changes like chest movement due to respiration and heartbeats. It is very sensitive, simple and a low-cost system but has a range limitation. Many researchers have utilized this technique for acquiring physiological signals. Gouveia et al., has studied bio continuous wave radar based human recognition system. In the study the authors have investigated the potential of the CW system for non-contact emotion detection. The respiratory signals of the subjects elicited with fear, happiness and neutral emotion were recorded. Machine learning algorithm such as SVM, KNN, and Random forest are utilized for performing emotion recognition [10]. This study concludes that bio radars technique is promising in emotion recognition application. Nebojša Malešević et al. have used 24 GHz continuous wave radar to acquire chest wall movement data of 21 volunteers. The ECG signal is used as a reference. To detect the variation is radar signal with heartbeat the ANN is trained using various topologies. The best performance was achieved with feed forward network. This method is highly suitable for real times applications [11].

B. Frequency Modulated Continuous Wave (FMCW) Radar

Frequency modulated continuous wave radar systems are capable of determining the distance and velocity of the target by transmitting a chirp (continuous frequency varying signal). The reflected signal from the target consists of a time delay. This variation in the frequency of the transmitted and the received signal is utilized for the measurement of distance and motion. The most common applications of this radar system are in healthcare, automotive and especially in the human emotion recognition by detecting the micro movements of chest. This technique provides an accurate measurement of even the small variations non-invasively. In comparison to the CW radar system FMCW radar systems are slightly complex and consumes more power. Despite a few limitations these radar systems are most widely used in the application of emotion recognition due to the high sensitivity of these systems.

FMCW systems like a 1T2R W-band radar provide high SNR for range detection [12]. Calibration facilities simulate kinematics, showing 77 GHz radars outperform 24 GHz in repeatability [13]. LSTM-based classification on FMCW signals detects targets with 95% accuracy [14]. These advancements reduce false alarms and improve resolution, but challenges include fabrication tolerances and environmental interference.

C. Ultra-Wideband (UWB) Radar

The UWB radar are capable of detecting very minute and slow movements by emitting a very short duration pulse in nanoseconds over a very wide frequency band typically above 500 MHz. It has the potential to measure even the millimeter range movements very accurately. In the human emotion recognition, the changes related to various emotions such as variation in the heart rate, respiration rate & its pattern and even the micro movement of the body can be detected using UWB radar. This technique offers high resolution, high accuracy, detection of micromovements, wide range, penetrates through clothes and hazy environments, non-contact, and safe for human beings. The challenges associated with the technique are it is more expensive as compared to the above-mentioned techniques, due to the use of wide frequency spectrum there may be regulatory limitations in some areas, do not penetrated through the walls and the furniture. Due to the minute motion sensitivity this is highly suitable for the human recognition application.

Table I Comparison of Radar Based Systems

Technique	Range	Advantages	Disadvantages	Applications
CW Doppler	0.5 – 2 m	Simple in design; High sensitivity	Susceptible to motion artefacts; low SNR	Contactless Heartbeat & respiration detection
FMCW	50 – 100 m	Simultaneous range; Good spatial resolution	Requires linear chirps, more complex design.	Gesture recognition, multi-person vital monitoring
UWB radar	1 – 20 m	Sensitive to micro-motions	Wideband front-end & sampling requirements	Inter-Beat Interval / HRV estimation.
Pulse Doppler	10 - 100 m	Strong long-range detection	High transmit power, complex RF design	Clutter effect

D. Doppler and Micro-Doppler effect

Quadrature Doppler radars with arctangent demodulation achieve high SNR (73.27 dB) for heartbeat detection, with 2.53-4.83% error in beat-to-beat intervals [15]. UWB radar senses arterial pulses cross-body, measuring PAT with high precision for PWV estimation [16]. Wearable radar with PPG estimates SBP with 98.2% accuracy in postures [17]. Heart sound detection uses 24 GHz DC-coupled radar for S1/S2 timing, correlating with ECG/PCG [18]. Array modules for bio-radars offer high gain for respiration/heartbeat separation [19]. Radar reflections from a person within the sensor's field of view are processed to extract a clean vital-Doppler signature. From this signature, emotional state is inferred, and an engagement score is calculated that reflects the individual's attentiveness or involvement in the ongoing activity. The comparative study of radar systems for biomedical applications to estimate physiological parameters wirelessly is tabulated in Table I.

III. Physiological Signal based Emotion Classification

Emotions trigger physiological changes, including alterations in heart rate, respiration, and cardiac waveforms. ECG signals capture these via electrodes, providing data on intervals like R-R peaks for HRV analysis. Radar systems, particularly millimeter-wave variants, detect micro-movements from chest walls or heartbeats without physical contact, using Doppler shifts or phase demodulation. Innovations in this domain emphasize noise reduction, feature optimization, and model training to achieve high accuracy. For instance, ECG methods often involve filtering to isolate emotional cues, while radar approaches focus on echo signal extraction and position optimization for reliable vital sign monitoring.

A. Heart rate

A non-contact radar sensor acquires cardiac signals. Relevant features are extracted from the heartbeat waveform, and a recognition module compares them against stored templates to verify or classification of emotional states. A non-contact heart-rate monitoring solution employs millimeter-wave radar to capture cardiac motion from the body surface. It acquires heartbeat waveforms, removes interference through filtering, and derives time-frequency representations. These representations serve as input to a trained convolutional neural network that computes sample entropy values. By evaluating entropy across different radar positions, the method automatically identifies the placement that yields the most stable signal, thereby achieving higher measurement accuracy. The technique gathers heart-rate traces from multiple body locations using a millimeter-wave radar, applies denoising, and feeds the cleaned waveforms into a fully convolutional network that was trained to recognize high-quality cardiac patterns. Sample entropy is calculated for each position; the location producing the lowest entropy is selected for continuous monitoring. This adaptive strategy significantly improves practical usability and measurement precision in everyday settings.

B. ECG based human recognition systems

A growing number of studies focus on identifying human emotions through electrocardiogram (ECG) recordings, especially for applications in mental health monitoring, stress detection, autism support, and affective disorder diagnosis. This technique first eliminates artifacts from raw ECG traces through filtering and normalization. It then extracts time-domain and frequency-domain characteristics that reflect typical heart-rate fluctuations linked to different emotional states. To reduce processing overhead, irrelevant attributes are removed using recursive feature elimination, while principal component analysis further compresses the data without sacrificing essential information. Any classifier model used can categorize the emotional condition, and a recommendation module subsequently suggests the detected mood to the user or caregiver. From a single-lead ECG, noise is removed and individual cardiac cycles are segmented at R-peak locations. Each cycle undergoes Gramian angular field transformation to create image-like representations. A PCA Net deep network helps in extraction of high-level features, which are then refined using Pearson correlation coefficients to discard redundant information. The filtered feature set is classified cycle-by-cycle, and majority voting across multiple cycles produces the final emotion label, achieving fast and cost-effective recognition.

Wireless acquisition of physiological features recorded using a radar-based system make the data acquisition more efficient and wireless that can enable real-time monitoring for smart healthcare systems. Chest-wall displacement caused by respiration and heartbeat can be captured remotely using FMCW radar. A suitable algorithm e.g., MVDR beamforming algorithm that helps in isolating echoes from the thoracic region. Phase demodulation yields the raw motion trace, from which breathing can be separated via bandpass filtering. Inter-beat intervals are measured, and a set of physiological indicators are computed. Any suitable classifier trained on these indicators delivers reliable emotion categorization while maintaining low environmental demands and rapid response.

Researchers have increasingly explored physiological markers beyond facial or behavioral cues for emotion recognition. The value of ECG as a robust biometric indicator that demands individualized models sensitive to minor deviations from a person's baseline. To raise both speed and accuracy, a novel Ensemble based decomposition technique can be used, that offers superior signal breakdown and classification performance compared to conventional methods. Wireless Acquisition of ECG signal through radar-based systems eliminates the need of on-body sensors and can provide real-time emotion detection without cumbersome process in subject's natural environment. A contact-free approach enables real-time identification of key ECG landmarks (P, Q, R, S, T waves) via millimeter-wave radar. Radar echoes and simultaneous conventional ECG recordings from the person is collected

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synchronously. Phase information from each heartbeat cycle is processed to isolate intrinsic mode components representing cardiac motion. The reference ECG is annotated with feature points, and semantic segmentation labels are generated. A deep learning network is trained on these paired datasets so that, during inference, it can directly locate ECG characteristic points solely from radar-derived heartbeat signals.

C. Data Acquisition and Preprocessing

Data acquisition and processing is a crucial step in the overall radar-based emotion classifier systems. The designing of antenna and signal processing techniques employed in emotion classifier systems affect the overall accuracy and precision achieved by the system. Series-fed microstrip arrays dominate 24 GHz designs due to their simplicity and integration potential. For instance, a 12×8 array achieves a voltage standing wave ratio (VSWR) below 1.5 and gain over 24 dBi from 24-24.25 GHz, with Chebyshev distribution reducing SLL to -16 dB in the E-plane [20]. Similarly, a 1×6 array with series feeding yields -26.5 dB SLL [21], while a 6×8 array with exponential distribution offers -19.1 dB SLL and 20.56 dBi gain [20]. Phased arrays enhance beam steering; an 8×12 array provides 1.1 GHz bandwidth and ±30° scanning with -18 dB SLL [22]. Butler matrix networks enable multi-beam formation; a 4×4 matrix with 1×12 arrays achieve flat-shoulder patterns for long/medium-range radar [23]. Lens-based designs, like a meta-surface lens, boost gain to 22.4 dBi with -21 dB SLL [24]. Waveguide slots offer high gain (e.g., 32-slot array at 15.19 GHz with low SLL) [25], and eco-friendly substrates like polypropylene yield compact arrays with -20 dB SLL [26]. Radar systems like Millimeter-wave radar operating in the 24-77 GHz frequency bands, offering advantages such as high spatial resolution and penetration through non-metallic materials, making it ideal for automotive and biomedical applications [20]. In automotive contexts, radars enable features like adaptive cruise control and blind-spot detection, while in biomedicine, they facilitate non-contact monitoring of cardiorespiratory signals [27]. Traditional sensors like ECG or photoplethysmography (PPG) require direct contact, limiting usability in dynamic scenarios, whereas radar provides unobtrusive alternatives [28]. A physiological signal like ECG which is a low frequency and low amplitude signal is very prone to the systemic noise; Hence, the technique of signal processing becomes highly crucial for overall performance of the system.

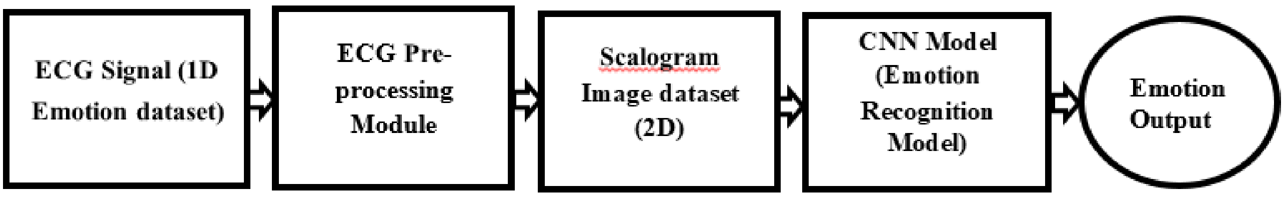

Fig. 3. ECG Scalogram based human emotion recognition system

The common signal processing techniques utilized by researchers are: Fast Fourier Transform (FFT), Short-Time Fourier Transform (STFT), Filtering with noise removal, Feature extraction techniques like time-domain, frequency-domain, and time-frequency analysis (wavelet transforms) as illustrated in Fig. 3.

IV. Machine Learning Methods

With advancement of Artificial Intelligence and machine learning, researchers have inclined towards answering the question if machine can access the human emotion precisely. Such emotion classifier systems can have wider applications in Human Machine Interaction Systems. Various classifier systems are developed and optimized using ensemble techniques to enhance the classification accuracy. Deep networks have been explored in great extent with various algorithms and hybrid convolutional networks have been proposed in literature in a quest of developing a highly accurate emotion classifier model. Some of the most common in the field are explained as follows:

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A. Support Vector Machines (SVM)

Support Vector Machine (SVM) is a supervised learning algorithm widely applied for classification problems owing to its ability to construct an optimal separating hyperplane that maximizes the margin between classes. By using kernel functions, SVM can efficiently handle complex and nonlinear relationships in data without explicitly increasing dimensionality. One notable strength of SVM is its good generalization ability even with limited training samples, which makes it attractive for fields such as emotion recognition. Researcher have demonstrated the usefulness of SVM in classifying emotional states from physiological and behavioral signals. For example, one study used heart rate variability features extracted from ECG signals during movie-elicited emotions and showed that SVM could classify both two and five emotional categories, indicating the feasibility of daily emotion monitoring using a single physiological signal (ECG-HRV) [29]. Similarly, in automatic speech emotion recognition, SVM has been applied to features such as MFCC and MEDC extracted from emotional speech databases, achieving high classification accuracies, including gender-dependent recognition with accuracies near or above 90%, highlighting its effectiveness for speech-based human computer interaction [30] [31][32]. Another work compared one-against-all and gender-dependent strategies using speech samples drawn from different corpora, confirming that SVM can discriminate among emotions like sadness, anger, fear, and happiness based on acoustic cues such as pitch and cepstral coefficients. Beyond speech and ECG, SVM has also been used on EEG-based emotion recognition systems, where experiments involving movie induction and feature extraction from frequency-domain EEG components reported satisfactory accuracies when compared with other classifiers such as multilayer perceptron or k-nearest neighbor. In addition, studies focusing on elderly emotion detection using pulse rate and SpO_2 signals have found that SVM outperforms k-NN and that combining multiple physiological features further improves accuracy and precision [33]. Altogether, these investigations illustrate that SVM is not only theoretically robust but also practically effective for multimodal emotion classification, reinforcing its relevance in contemporary affective computing and human-centered technologies. Although SVM performs well with high-dimensional data, its training time increases significantly as the dataset grows, making it less suitable for very large datasets. Choosing the right kernel and tuning parameters like C and γ can also be difficult and usually requires experimentation. Furthermore, SVM may struggle when classes are highly overlapping or when data contains too much noise, reducing classification accuracy.

B. *Random Forests*

Random Forest is a widely used ensemble learning algorithm that builds multiple decision trees and combines their predictions to achieve higher accuracy and improved generalization compared to a single model [34]. The method randomly selects subsets of samples and features while constructing each tree, which helps reduce overfitting and enables the model to capture nonlinear relationships [35] [36]. Because of its robustness and relatively simple implementation, Random Forest has gained popularity in many classification tasks including human emotion recognition. Several studies have investigated its potential for analyzing physiological signals, particularly EEG. For instance, work involving multi-wavelet features extracted from multichannel EEG recordings reported very high recognition rates for emotions such as happiness, sadness, excitement, and hate when Random Forest was used as the classifier [37]. Similarly, empirical mode decomposition combined with nonlinear features such as entropy and fractal dimension demonstrated that Random Forest could classify positive, neutral, and negative emotions with accuracies exceeding 89%, outperforming some traditional approaches [38]. Random Forest has also been successfully applied to vocal-based emotion recognition. Experiments using prosodic and spectral speech features achieved higher recognition performance compared with linear discriminant analysis and some deep learning models, demonstrating the algorithm's ability to discriminate between emotions such as happiness, fear, sadness, and surprise [39]. In facial emotion recognition, modified versions such as partitioned random forests have been proposed, showing improved accuracy even on smaller datasets by learning more complex decision boundaries [40]. Overall, these results highlight Random Forest as a flexible, reliable, and effective classifier for multimodal emotion analysis. Although Random Forest reduces overfitting compared to a single decision tree, it can still become complex and computationally expensive when a large number of trees are used. In addition, interpreting the internal decision process can be difficult because the ensemble behaves like a "black box." Finally, Random Forest may struggle when features are highly correlated, which can affect variable importance measures.

C. k-Nearest Neighbors (k-NN)

k-Nearest Neighbors (k-NN) is a classical machine learning approach widely used for classification and regression tasks due to its simplicity and non-parametric nature. Instead of building an explicit model during training, k-NN classifies new samples based on similarity to existing instances, making it highly intuitive and adaptable to diverse feature types. Its ability to work effectively with physiological signals has made it increasingly relevant in healthcare analytics and emotion recognition. For instance, studies combining ECG and PCG signals have shown that extracting statistical features such as wavelet coefficients and Mel-frequency cepstral coefficients, followed by k-NN classification, enhances diagnostic accuracy compared to processing each signal independently [41]. k-NN has also been applied for early detection of baby blues syndrome, where heart rate variability measures derived from wearable sensors were classified with encouraging accuracy, demonstrating its suitability for clinical environments with small datasets [42]. In stress recognition research, EEG-based features have been used with k-NN to distinguish between relaxed and stressed states, achieving highly reliable classification performance [43]. Similarly, arrhythmia detection using ECG signals has benefited from careful hyperparameter tuning—modifying distance metrics, neighbor counts, and weighting functions—to improve accuracy, precision, and F1-scores, highlighting k-NN's sensitivity to parameter selection [44]. Recent work has further addressed common limitations such as class imbalance and boundary misclassification by introducing enhanced versions like weighted and boundary-aware k-NN algorithms that adjust feature contributions and voting mechanisms, leading to significant gains in accuracy for multi-emotion recognition from physiological signals [45]. Although k-NN is simple and intuitive, it becomes computationally expensive with large datasets because every classification requires distance computation. Performance is highly dependent on the choice of k, feature scaling, and distance measure. Moreover, k-NN can struggle with imbalanced classes and noisy features, which may lead to misclassification.

D. **Deep Learning Approaches**

Convolutional Neural Networks (CNNs) are deep architectures capable of learning hierarchical and spatially localized representations through stacked convolutional layers, nonlinear activations, and pooling operations. They reduce reliance on hand-crafted feature extraction by automatically identifying task-relevant patterns, which is particularly useful when signals exhibit complex temporal and spectral structures. Although CNNs are widely used in image analysis, recent studies show significant potential in human state and emotion recognition using physiological signals, where subtle variations appear in time–frequency or sequential forms. Several recent investigations demonstrate that converting bio-signals into image-like representations such as scalograms or spectrograms allows CNNs and their variants to learn discriminative emotional or behavioral patterns. Research using EEG signals has demonstrated that transforming them into continuous wavelet-based time–frequency images enables deep models, including GoogLeNet, to capture emotional characteristics with high discriminative accuracy [46]. Similar trends appear in studies using ECG and galvanic skin response signals, where pretrained CNNs such as MobileNet, NASNetMobile, DenseNet, and Inception-ResNet variants achieved strong results in both valence and arousal classification across individual and group settings [47]. Attention-enhanced CNN architectures further highlight that incorporating spatial and channel-wise focus helps model subtle physiological variations, achieving state-of-the-art recognition on multiple public datasets [48]. Beyond emotion analysis, CNNs combined with recurrent units such as LSTM or Bi-LSTM have been shown to extract time-dependent cardiac information, supporting clinically relevant classification of cardiovascular conditions with promising accuracy and F1-scores [49]. Contactless and wearable-based sensing such as PPG and ECG also demonstrate feasibility for automatic emotion recognition, showing encouraging results even under naturalistic conditions [50].

Despite these advances, several challenges remain, including substantial inter-subject variability, dependency on sensor placement and acquisition conditions, and limited generalization across diverse datasets [51]. Furthermore, computational complexity, availability of large annotated physiological datasets, and the difficulty of explainability continue to constrain large-scale deployment.

E. Recurrent Neural Networks (RNNs),

Recurrent Neural Networks (RNNs) form a family of deep learning architectures specifically designed to model sequential patterns and temporal dependencies in data [52]. Unlike feed-forward networks, RNNs incorporate feedback connections that allow information from previous time steps to influence the current output, making them highly suitable for processing physiological signals, speech, and time-series [53]. Modern variations such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) further improve the learning of long-term dependencies by integrating gating mechanisms that control information flow through time. Because many physiological and emotional signals evolve dynamically, RNN-based approaches have become increasingly relevant in human-centered computing [54]. Recent studies demonstrate promising emotion recognition performance when RNNs are applied to EEG signals collected in brain–computer interface applications. For instance, comparative evaluations using generic RNN, LSTM, and GRU architectures have reported high accuracies for binary emotion classification, suggesting that recurrent models effectively capture discriminative temporal features in EEG recordings [55]. Beyond emotion recognition, recurrent architectures also show significant value in biometric authentication using ECG signals, where they have outperformed traditional methods such as SVMs and PCA. In particular, bidirectional LSTM-based recurrent frameworks have been shown to deliver near-perfect precision, recall, and F1-scores across publicly available datasets, highlighting the ability of RNNs to capture directionally rich temporal structure relevant to personal identification [56]. More recent hybrid models combine convolutional layers with LSTM to integrate spatial, spectral, and temporal information simultaneously. These convolutional-recurrent architectures have demonstrated state-of-the-art accuracy on well-established EEG emotion datasets such as SEED and DEAP, emphasizing the benefit of jointly modeling frequency content and temporal evolution of emotional responses [57]. Overall, these findings indicate that recurrent networks, especially when fused with convolutional components, offer strong potential for next-generation physiological analysis systems [58]. Despite these advantages, several challenges remain, including susceptibility to overfitting, computational cost during training, and difficulties in generalizing across subjects, sensor types, and recording environments. Additionally, interpreting recurrent decisions remains a key limitation for clinical or security applications requiring explainability.

F. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network designed to learn long-range temporal dependencies by incorporating memory cells and gating mechanisms that regulate the flow of information over time [59]. In radar-based human recognition, motion signatures such as micro-Doppler, gait cycles, and subtle limb dynamics evolve sequentially, making LSTMs highly suitable for extracting discriminative temporal patterns from radar echoes. Recent IoT-enabled frameworks have demonstrated that LSTM-based emotion or physiological recognition can operate in real time and support remote healthcare communication under constrained conditions [60]. Other studies have shown that LSTM models trained on peripheral physiological signals including heart rate, temperature, and electrodermal activity can effectively classify human emotional states with high accuracy, even in subject-independent settings [61]. Beyond emotion understanding, LSTM networks have also been successfully employed in biomedical identification tasks, such as ECG-based person recognition, by learning intra-beat and inter-beat variations without relying on manually detected fiducial points [62]. Collectively, these findings suggest that LSTMs hold strong promise for radar-based human recognition, where temporal continuity is a dominant characteristic of human motion. However, LSTMs require extensive training data, are computationally intensive, and may suffer from overfitting when applied to small or highly variable datasets. This is a limitation for radar applications deployed in real-world environments. End-to-end deep learning architectures trained directly on radar spectrograms remove the need for hand-crafted micro-Doppler descriptors by learning optimal time–frequency features from raw or minimally processed radar returns. Convolutional and convolutional recurrent networks applied to spectrogram inputs (STFT/micro-Doppler or CWT) have shown strong performance for activity, gait and identity recognition, often outperforming classical feature plus classifier systems. Nevertheless, end-to-end spectrogram systems are data-hungry, sensitive to spectrogram resolution and radar hardware differences, and can suffer domain shift across sensors and environments motivating transfer learning, domain adaptation and denoising/preprocessing strategies in contemporary work.

G. Performance metrics of Deep Network Emotion Classifier Models

A CNN based trained model suitability are measured in terms of the model performance parameters and accordingly the hyperparameters are tuned to select an optimized and highly suitable emotion classifier model. Some of the crucial performance metrics calculated on the confusion matrix of the validation dataset. The parameters are calculated using True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) values in the confusion matrix plot of the test dataset to evaluate the model parameters to ensure the generalizability of the trained CNN model.

Accuracy: Accuracy provides an overall measure of how often a classifier is correct. It considers both positive and negative predictions and is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In balanced datasets, accuracy gives a reliable indication of system performance, but in imbalanced medical data, it may be misleading, as a classifier could appear accurate while failing to detect minority cases. For example, if most ECG samples are normal, a classifier predicting all samples as normal may show high accuracy while missing abnormal condition entirely. Therefore, accuracy should be interpreted together with class-sensitive metrics in biomedical applications.

Precision: Precision expresses the proportion of predicted positive cases that are truly positive:

$$Precission = \frac{TP}{TP + FP}$$

It is particularly relevant when false positives impose unnecessary clinical risks, emotional stress, or economic burden. For example, in postpartum depression screening, incorrectly labeling healthy mothers may lead to avoidable evaluations. Precision becomes useful where the cost of false alarms is high, especially in screening large populations. Models with high precision demonstrate reliable positive predictions, although precision alone does not reflect the ability to capture all diseased cases. Thus, precision is typically interpreted together with recall to provide a balanced overview of diagnostic efficiency in healthcare classification tasks.

Recall: Recall, commonly called sensitivity in clinical literature, measures how effectively a classifier identifies actual positive cases:

$$Recall = \frac{TP}{TP + FN}$$

High sensitivity is crucial when missing diseased individuals may delay treatment or increase clinical risk. For example, failing to detect ECG abnormalities can expose cardiac patients to serious complications. Screening systems typically prioritize sensitivity even if this increases false positives, because minimizing missed diagnoses is often more critical than avoiding false alarms. Consequently, sensitivity is frequently emphasized in early detection systems, intensive-care monitoring, and maternal mental-health assessment, where identifying true positive patients is a primary safety requirement.

F1-score: The F1-score combines precision and recall into a single, balanced measure using the harmonic mean:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

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It penalizes extreme imbalance, making it particularly relevant when classes are unevenly distributed. In emotion recognition or diagnostic screening, a classifier may either detect many positives (high recall) or maintain a low false-positive rate (high precision). The F1-score reflects the trade-off between these behaviors and provides a more realistic evaluation than accuracy in biomedical data, which often exhibits class imbalance. Therefore, the F1-score is widely adopted in EEG, ECG, and physiological state-recognition studies.

Specificity: Specificity measures the proportion of correctly identified negative cases:

$$Specificity = \frac{TN}{TN + FP}$$

This metric is fundamental when distinguishing healthy subjects from pathological findings. High specificity reduces unnecessary medical intervention and prevents misclassification-driven stress. For instance, in arrhythmia detection, a classifier that incorrectly labels normal cardiac patterns as abnormal may increase clinical workload. Therefore, specificity complements sensitivity, and both must be evaluated together. An appropriate diagnostic system balances disease detection with avoidance of excessive false alarms.

FPR: The False Positive Rate (FPR) quantifies how frequently healthy instances are mistakenly detected as diseased:

$$FPR = \frac{FP}{FP + TN}$$

FPR is directly related to specificity, since FPR=1−Specificity. A high FPR increases unnecessary examinations and burden on healthcare systems. For example, in postpartum mental-health screening, frequent false alarms may lead to inappropriate psychological referral. FPR therefore indicates screening reliability and economic practicality, especially in large-scale public-health applications.

FNR: False Negative Rate describes how often actual positive cases are missed:

$$FNR = \frac{FN}{TP + FN}$$

In healthcare, a high FNR can be dangerous because undetected patients may remain untreated. For example, missing stress-related abnormalities in EEG may delay clinical intervention. Thus, minimizing FNR is essential for safe clinical deployment.

TPR: True Positive Rate (TPR) represents how effectively a classifier detects positives and is mathematically equivalent to sensitivity:

$$TPR = \frac{TP}{TP + FN}$$

A high TPR is critical in screening systems requiring early intervention, such as cardiovascular monitoring, postpartum depression detection, and EEG-based stress analysis.

TNR: True Negative Rate (TNR) captures the proportion of correctly classified healthy cases:

$$TPR = \frac{TN}{TN + FP}$$

A balanced diagnostic model should maintain both high TNR and high TPR to ensure reliable discrimination in medical applications.

V. Future Scope and Recommendation

Development of real-time, low-power embedded radar systems for ECG data acquisition using wireless techniques need further improvement in signal processing techniques. The accuracy of radar-based systems in reconstruction of ECG signal needs further research and improvement. One of the possible methods is increase in frequency of operation like ISM Frequency band shifting. It enables better

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separation between chest displacement and heartbeat movement in ECG reconstruction using mechanical movement of human chest. Moreover, Inter-patient variability requires adaptive models; combining radar/ECG enhances robustness [63]. Phase based heartbeat extraction techniques can be employed using phase wrapped networks. Sophisticated algorithms need to be developed to mitigate motion artefacts for which deep spatial-temporal technique is one of an effective choice. Furthermore, the multimodal features help in achieving greater accuracy but single modal systems like ECG based emotion classifiers will enable us in having real-time emotion recognition in smart wearable healthcare systems. ECG based single modal classifier systems in smart wearables like smartwatches, health bands etc. can be possible if the acquisition of ECG through such systems get clinical acceptance. Hence, the improvement in accuracy of ECG acquisition offers a huge room of improvement. Classifier model's optimization and generalizability need special attention because implementation of such systems like FPGA boards requires optimization to reduce memory requirement, computation complexity as well as the latency to enhance the speed of detection of emotion while the wearable is acquiring the ECG data in real time. For such improvements, transfer learning and domain adaptation for robust models can serve as a viable option. Last but not the least, ethical considerations and privacy concerns need redressal as well as the generalizability of model needs to such extent that it could beat the cultural and contextual bias, it needs varied dataset for training and validation.

VI. Conclusion

Radar-based emotion recognition is a rapidly growing field that offers significant advantages over traditional modalities. Despite current challenges, advancements in radar technology, machine learning, and signal processing are steadily improving the feasibility and accuracy of these systems. Human emotions influence behavior, decision-making, and well-being, making their accurate detection essential for applications in psychology, healthcare, and user experience design. Traditional methods rely on facial expressions or self-reports, which can be subjective or intrusive. Physiological signals, such as heart rate variability (HRV) derived from ECG or radar-detected cardiac activity, offer objective alternatives by capturing autonomic nervous system responses. This review highlights radar based human emotion recognition systems using physiological signals like ECG. ECG-based systems analyze electrical heart activity, while radar methods enable non-contact monitoring via electromagnetic waves. The report reflects rapid advancements in machine learning and sensor fusion.

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