



OPEN RF sensing enabled tracking of human facial expressions using machine learning algorithms

Hira Hameed¹, Mostafa Elsayed¹, Jaspreet Kaur¹, Muhammad Usman², Chong Tang¹, Nour Ghadban¹, Julien Le Kernec¹, Amir Hussain³, Muhammad Imran¹ & Qammer H. Abbasi^{1,4}✉

Automatic analysis of facial expressions has emerged as a prominent research area in the past decade. Facial expressions serve as crucial indicators for understanding human behavior, enabling the identification and assessment of positive and negative emotions. Moreover, facial expressions provide insights into various aspects of mental activities, social connections, and physiological information. Currently, most facial expression detection systems rely on cameras and wearable devices. However, these methods have drawbacks, including privacy concerns, issues with poor lighting and line of sight blockage, difficulties in training with longer video sequences, computational complexities, and disruptions to daily routines. To address these challenges, this study proposes a novel and privacy-preserving human behavior recognition system that utilizes Frequency Modulated Continuous Wave (FMCW) radar combined with Machine Learning (ML) techniques for classifying facial expressions. Specifically, the study focuses on five common facial expressions: Happy, Sad, Fear, Surprise, and Neutral. The recorded data is obtained in the form of a Micro-Doppler signal, and state-of-the-art ML models such as Super Learner, Linear Discriminant Analysis, Random Forest, K-Nearest Neighbor, Long Short-Term Memory, and Logistic Regression are employed to extract relevant features. These extracted features from the radar data are then fed into ML models for classification. The results show a highly promising classification accuracy of 91%. The future applications of the proposed work will lead to advancements in technology, healthcare, security, and communication, thereby improving overall human well-being and societal functioning.

Facial recognition technology has witnessed substantial advancements in recent years, finding widespread applications across various domains. These applications include healthcare and mental health, human-robot interaction, biometric identification, human-computer interaction, security and surveillance, as well as entertainment and gaming. It is also treated as a nonverbal sign used by people to convey emotions, intentions, and social signals¹. The paper² presents that understanding and monitoring facial expressions has piqued the interest of researchers in a variety of fields, including psychology, neuroscience, and computer vision.

Face expressions are ubiquitous and may be used to communicate effectively across cultures and languages³. They are essential in social interactions because they let humans express emotions such as happiness, sadness, anger, fear, surprise, disgust, and contempt⁴. Facial expressions are caused by the coordinated movement of facial muscles, which results in recognized and interpretable patterns by human observers⁵. Affective computing, human-computer interaction, healthcare, and social robotics all benefit from the capacity to reliably monitor and comprehend facial emotions⁶.

Camera-based face expression monitoring systems are substantial. These systems rely on cameras to capture facial photos or videos, which are then analyzed to determine facial expressions. Many studies have presented several algorithms to effectively recognize and classify face expressions, including classic computer vision approaches and deep learning techniques^{7–9}. In this paper¹⁰, the framework integrates edge computing and optimized mobile network design to enable efficient and real-time facial expression recognition on mobile devices. The author¹¹ presented a system that utilizes PTZ cameras and the Faster R-CNN algorithm for facial expression analysis and student engagement recognition. It described the system's architecture, training process, and experimental results, highlighting its potential contributions to the field of educational technology and

¹University of Glasgow, James Watt School of Engineering, G12 8QQ Glasgow, UK. ²School of Computing, Engineering and Built Environment, Glasgow Caledonian University, Glasgow G4 0BA, UK. ³School of Computing, Edinburgh Napier University, Scotland, UK. ⁴Artificial Intelligence Research Center (AIRC), Ajman University, Ajman, UAE. ✉email: qammer.abbasi@glasgow.ac.uk

classroom management. Camera-based systems provide high-resolution facial images, allowing for a thorough analysis of facial traits. Camera-based systems have significant drawbacks, for example, require subjects to be inside the field of view and may be affected by lighting conditions, privacy issues, occlusions, and the requirement for direct line-of-sight¹². These constraints can limit the usability and accuracy of camera-based solutions, especially in uncontrolled or real-world environments.

Wearable gadgets such as smart glasses, headphones, and wristbands have been investigated as alternate platforms for monitoring facial expressions¹³. Sensors such as accelerometers, gyroscopes, and electroencephalography (EEG) sensors are used in these devices to gather physiological data linked with face muscle movements¹⁴. Researchers built algorithms to infer face expressions by examining the collected data¹⁵. Wearable technology provides the benefit of portability as well as the capacity to observe face expressions in real-time throughout regular activities. They do, however, have restrictions¹⁶. Wearable technologies can be obtrusive, inconvenient, and deliver inaccurate or incomplete data. Furthermore, sensor installation and calibration might be difficult, resulting in significant mistakes in face expression interpretation¹⁷. A major limitation of wearable-based facial expression recognition is its interference with daily routines, as individuals are required to constantly carry and wear the devices.

In contrast, radio frequency (RF) facial expression sensors present a promising solution to meet the requirements of next-generation technologies. These sensors utilize RF sensing and machine learning (ML) techniques to accurately detect and recognize facial expressions, offering valuable cues that can benefit a wide range of applications. The paper discusses the design considerations, circuit architecture, and implementation details of the RF waveform generation and acquisition circuits. The proposed circuits are evaluated and validated through experimental results, demonstrating their suitability for radar system applications¹⁸. These approaches collect and analyse facial muscle movements and electromagnetic scattering patterns induced by facial expressions using RF signals¹⁹. The author²⁰ discusses RF sensing technologies for monitoring various health-related parameters such as respiration, heart rate, activity level, and sleep quality. They explore different RF-based sensing techniques, including Doppler radar, RFID, and Wi-Fi sensing, highlighting their respective advantages and limitations. RF signals can pass through impediments like clothing and walls, enabling continuous monitoring in uncontrolled conditions^{21,22}. The author²³ used wireless signals, specifically the channel state information (CSI) gathered from Wi-Fi devices, to detect the subtle alterations in the environment resulting from human emotional states. The classification accuracy achieved for emotions was 71.67%. The paper presents the architecture and working principle of the WiFace system, which involves capturing and analyzing the variations in Wi-Fi signals reflected off a person's face. A total of six activities were performed by the subject Happy, Fearful, Surprised, Happily surprised, Angriily surprised, and Fearfully surprised²⁴. Table 1 shows the comparison between vision-based and sensor-based technology for facial expression recognition.

The following presents the main contributions of our research work in the field:

- RF technology enhances facial expression applications through non-intrusive, privacy-preserving monitoring, and remains effective even in poor lighting conditions, ensuring accurate detection across various environments.
- We proposed a unique RF sensing-based facial expression monitoring system that integrates powerful machine learning algorithms for accurate facial expression recognition and is applicable for different applications such as healthcare and mental health, human-robot interaction, biometric identification, human-computer interaction, security and surveillance, as well as entertainment and gaming.
- A dataset comprising 1,000 samples was gathered, encompassing five distinct facial expressions because these are the most common and part of normal routines. The data collection took place at a consistent distance of 1.50 meters from the target. To ensure variability and inclusiveness, four participants were involved in the data collection process. These participants consisted of two males and two females within the age range of 20 to 40 years, all belonging to different ethnic backgrounds, including Chinese, Asian, and English.
- We used extensive experiments and comparisons with existing camera-based and wearable device-based technologies to assess the performance and usefulness of the proposed RF-based system, demonstrating the benefits and prospective uses of RF sensing in facial expression monitoring.
- In this study, we have presented the experimental results of several advanced machine learning models applied to our benchmark dataset. These findings provide valuable insights and can serve as a fundamental

References	Technology used	Activity used	AI model	Accuracy (%)
²⁵	Vision-based	Facial expression	ResNet-50	95.39 ± 1.41
¹⁰	Vision-based	Facial expression	DNN	85.57
²⁶	Vision-based	Facial expression	3D-CNN and ConvLSTM	98.83
²⁷	Vision-based	Facial expression	DBN	96.25
²⁸	Sensor-based	Facial muscle movements	Cross-domain transfer learning	80.75
²⁹	Sensor-based	Emotion recognition	Random Forest	60–70%
³⁰	Sensor-based	Respiration and heart rate signals with emotion recognition	CNN and GRU	84.5% and 74.25%
³¹	Sensor-based	Emotion recognition	Neural network	80.59
Our	Sensor-based	Emotion recognition	LSTM	91.0%

Table 1. Comparison of vision-based and sensor-based emotion recognition with our work.

reference for future research in the domain of facial expression detection. This research introduces innovative facial expression gestures using radar-sensor and micro-doppler signatures. The study focuses on five distinct gestures: Neutral, Happy, Sad, Fear, and Surprise. Experimental data is collected using an FMCW radar, and the recorded data is represented as a Micro-Doppler signal. The classification accuracy achieved is 91.0%. The potential applications of this technology are illustrated in Fig. 1. Detailed information regarding the setup, data collection process, machine learning algorithms, and experimental results are provided in the subsequent sections.

Methodology

The methodology used in this study is depicted in Fig. 1 as a block diagram. The framework comprises three main steps. Firstly, diverse facial expression datasets were collected, constructed, and annotated using FMCW radar. Subsequently, the pre-processing phases are explained in the second step, as depicted in Fig. 2. Finally, a range of machine learning models was employed for the classification of facial expressions. The following subsections provide a detailed discussion of each stage in the proposed methodology.

Experimental setup and data collection

The hardware configuration of the radar-based facial expression system is illustrated in Fig. 3. The experiments were conducted in two separate rooms, as shown in Fig. 3a,b, representing Room 1 and Room 2, respectively. The experimental setup included a Frequency Modulated Continuous Wave (FMCW) radar sensor, positioned in front of the user. The FMCW radar sensor comprised a transmitter (Tx), a receiver (Rx), and two horn antennas for transmitting and receiving, allowing for a maximum detection range of 20 meters. The key parameter settings of the radar system are outlined in Fig. 4a. During the facial expression tasks, the subject was positioned at a distance of 1.50 meters from the radar. The subject's body remained in a natural position, with the only movements being those of the face and slight head movements, which are typical during the conversation. A single subject facial expression was recorded for each action in the study for a total of 4 s. The radar system transmitted and received the RF signal during this time period. Figure 5b presents the range time output captured during the measurement of various facial expressions. This output is utilised for signal processing and distance measurement purposes. To extract features from the radar data, the Fast Fourier Transform (FFT) is applied, generating spectrograms that illustrate the radar Doppler shift caused by facial movements as depicted in Fig. 5c. The analysis of these spectrograms reveals variations corresponding to different facial expressions due to the distinct movements of the face and mouth. The use of a trigger in a radar system is essential to ensure precise timing, synchronization, and control over the data acquisition process, as shown in Fig. 6.

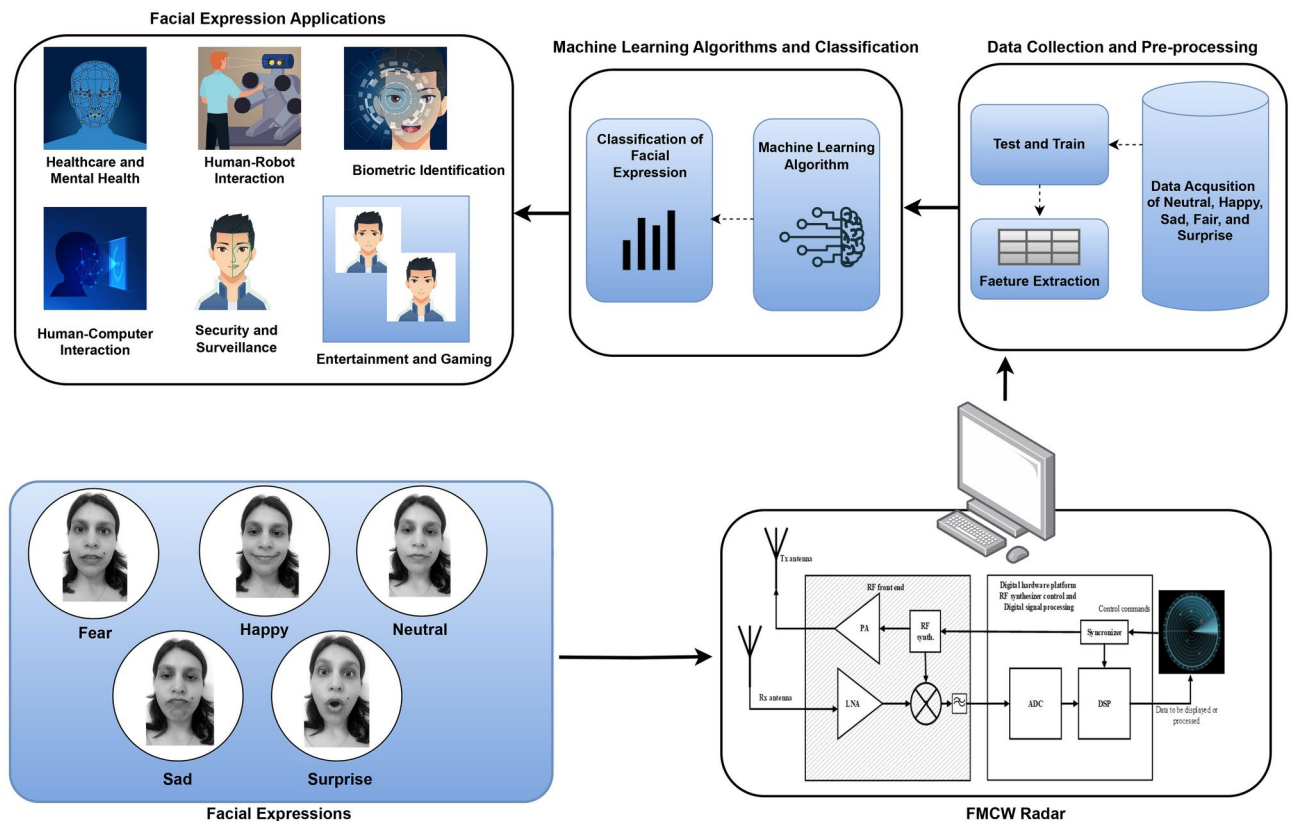


Fig. 1. The overall flow diagram of proposed facial expressions system.

Algorithm 1 Algorithm for Range-Time Map Generation and Classification

```

1: procedure RANGETIMEMAPGENERATION( $F_b$ )
2:   Input: Beat frequency  $F_b$ 
3:   Output: Range-time map  $X$  (number of chirps  $\times$  samples per chirp)
4: end procedure
5: procedure MODELREPRESENTATION
6:   Denoising algorithm
7:   FFT (Fast Fourier Transform) for range estimation (Vectorized)
8:   Target detection
9:   Doppler processing for detected targets (Parallelized)
10:  Send results through Ethernet for data processing
11: end procedure
12: procedure CLASSIFICATION( $X$ )
13:   Input: Input space  $X$ 
14:   Output: Output space (Classes)  $Y$ 
15:   Training data: Parallelized data loading and processing
16:   Hypothesis space
17:   Learning algorithm:  $A$ 
18: end procedure
19: procedure LEARNINGPROCESS( $h(x)$ )
20:   Parallelized hypothesis selection by  $A$ 
21:   Loss function:  $L(y, h(x))$  (Measures classification error)
22: end procedure
23: procedure TRAININGPHASE
24:   Parallelized data batching and processing
25:   Minimize empirical risk:  $R_{\text{emp}}(h) = \frac{1}{n} \sum_{i=1}^n L(y_i, h(x_i))$ 
26: end procedure
27: procedure EVALUATIONANDTUNING( $x_{\text{test}}, y_{\text{test}}, \Theta$ )
28:   Initialize best hyperparameters  $\theta_{\text{best}}$ 
29:   Initialize best evaluation metric (e.g., accuracy)  $e_{\text{best}}$ 
30:   for each  $\theta \in \Theta$  do
31:     Perform  $k$ -fold cross-validation with hyperparameters  $\theta$ 
32:     Compute the average cross-validation performance metric
33:     if cross-validation metric is better than  $e_{\text{best}}$  then
34:       Update  $e_{\text{best}}$  with the new metric value
35:       Update  $\theta_{\text{best}}$  with the current hyperparameters  $\theta$ 
36:     end if
37:     Perform other technique (e.g., grid search, random search) with hyperparameters  $\theta$ 
38:     Compute the performance metric for the other technique
39:     if other technique metric is better than  $e_{\text{best}}$  then
40:       Update  $e_{\text{best}}$  with the new metric value
41:       Update  $\theta_{\text{best}}$  with the current hyperparameters  $\theta$ 
42:     end if
43:   end for
44:   Select the best hyperparameters  $\theta_{\text{best}}$  based on both techniques
45:   Train the final model using the entire dataset and  $\theta_{\text{best}}$ 
46:   Save the trained model to a file
47: end procedure

```

Fig. 2. Pseudo code for the proposed facial expression systems.**Dataset**

In this phase, facial expression data was collected using FMCW radar. Figure 3 illustrates the hardware setup of the radar-based system employed for facial expression data collection. The FMCW radar sensor was equipped with two horn antennas, one for transmission (Tx) and the other for reception (Rx), enabling a maximum detection range of 20 meters. As shown in the figure, the radar sensor is placed on the table. The key parameter settings of the radar are indicated in the Fig. 4a. In order to encompass different complexity levels in the dataset, it was recorded in two different room environments. Because data collection is significantly impacted



Fig. 3. The experimental setup. (a) The experimental setup for room 1. (b) The experimental setup for room 2.

Parameter	Value
Sensor Type	FMCW Radar
Center Frequency	9.5 GHz
Bandwidth	1GHz
Chirp Width	50 us
Chirp Repitation Period	100 us
Transmitter Power	23 dBm
Reciever Gain	20 dB
Tx and Rx Type	Horn Antenna
Antenna Gain	13 dB
Number Of Samples Per Class	30
Distance From Rdar to Target	1.5 meter
Activity Duration	4 sec

Classes	Experimental Dataset				
	Subject (S1)	Subject (S2)	Subject (S3)	Subject (S4)	Total
Happy	50	50	50	50	200
Sad	50	50	50	50	200
Surprise	50	50	50	50	200
Fair	50	50	50	50	200
Neutral	50	50	50	50	200
Total	250	250	250	250	1000

ML Model	Parameters	Settings
Super Learner	N_estimator	20
	Type	Multi-threading
	N_split	10
	Solver	Liblinear
Linear Discriminant Analysis	Gamma	Scale
	Solver	Svd
	Shrinkag	None
	Store_covariance	False
	Tol	0.0001
Random Forest	CV	10
	Covariance_estimator	None
	N_estimator	200
	Criterion	gini
K Nearest Neighbour	Mini_samples_Split	2
	Max_features	sqrt
	N_neighbors	5
	CV	20
	Weights	Uniform
Long Short-Term Memory	Leaf Size	30
	Metric	minikowski
	Learning rate	0.0001
	Batch size	128
Logistic Regression	Learning algorithm	Adam
	Loss function	Binary_crossentropy
	Number of epochs	100
	Penalty	l2
	tol	0.0001
Logistic Regression	Solver	lbfgs
	CV	10
	C	1.0

Fig. 4. (a) Selected hardware and software parameter settings. (b) A summary of the collected data, the participant count, and the conducted activities of facial expressions. (c) Parameter settings for the ML models.

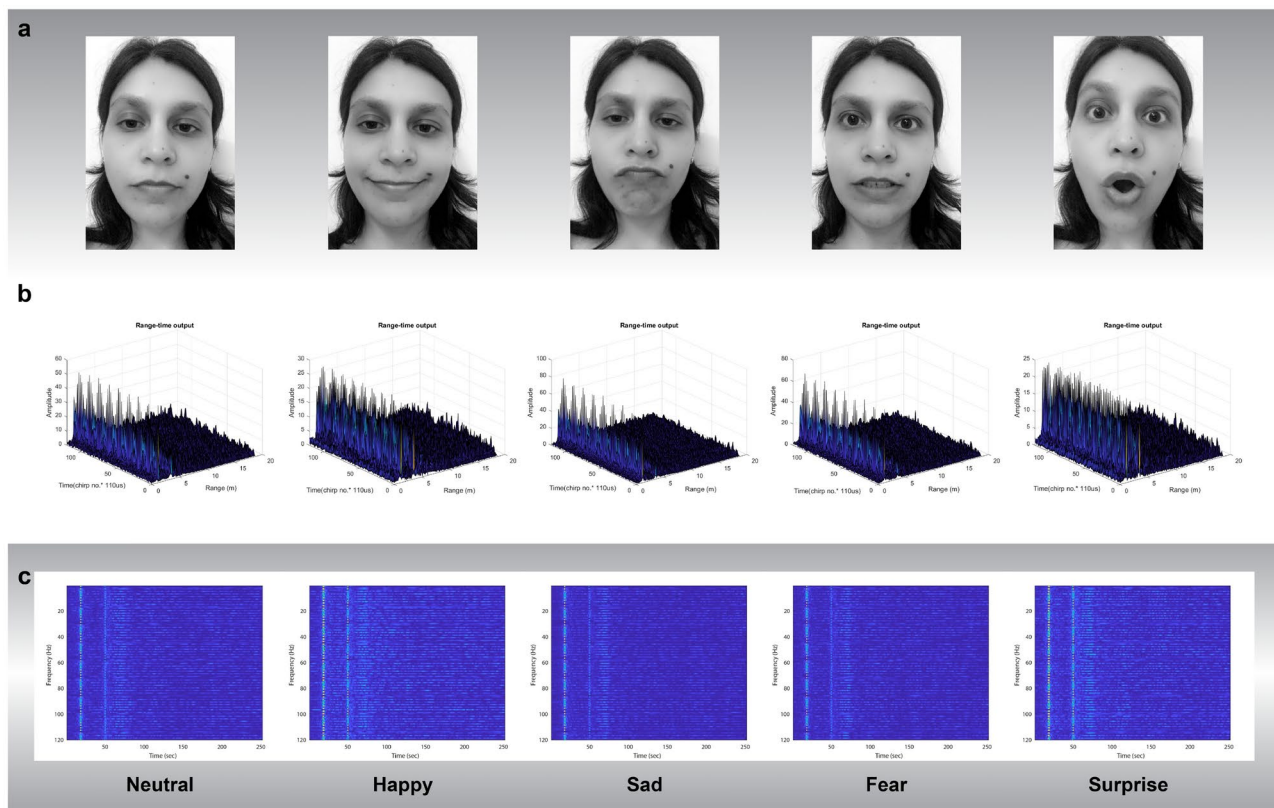


Fig. 5. The radar signal representation of facial expression activities. **(a)** A visual representation of facial expression activities. **(b)** The range-time output of various activities **(c)** Spectrogram representing various facial expression activities.

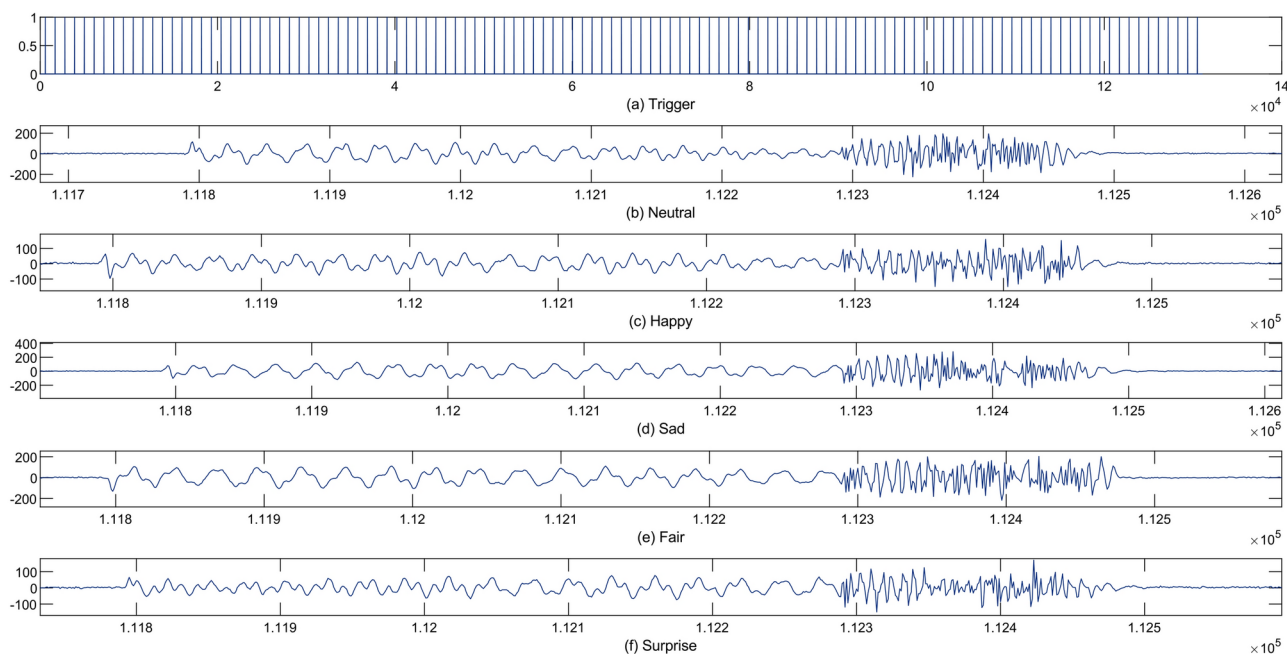


Fig. 6. A visual representation of variation in frequency for different facial expressions **(a)** Trigger. **(b)** Neutral. **(c)** Happy. **(d)** Sad. **(e)** Fair. **(f)** Surprise.

by a variety of environmental circumstances, ensuring the reliability and authenticity of the proposed system in a variety of locations. After collecting the dataset, it is proof that the system has the same behaviour in all environments. During the data collection process, the subjects maintained a neutral body position, focusing solely on facial movements. Additionally, each activity had a fixed duration of 4 s, allowing for the collection of data corresponding to a single gesture performed by an individual subject. Figure 5 provides a visual illustration of the face expression datasets. We have obtained ethical approval for the study, confirming that all research was conducted in accordance with relevant guidelines and regulations. Due to the nature of the work, informed consent was obtained from all participants for the use of identifying information and images in an online open-access publication. This approval was granted by the College of Science and Engineering at the University of Glasgow's Research Ethics Committee, under approval numbers (300200232 and 300190109). The data collection process involved the participation of four individuals, consisting of two males and two females. The inclusion of multiple participants aimed to enhance the realism and diversity of the dataset. A total of 1000 data samples were collected during the experiment, encompassing five distinct categories across two different rooms. The details of the collected dataset are highlighted in the Fig. 4b. In each experiment, a total of 1000 data samples were collected from four participants, with 30 samples collected in each class. In particular, each participant repeated the facial expression activity of each gesture 30 times with the radar. In this way, each participant contributed to collecting 250 data samples in total for the fifth class. In each case, a total of 1000 data were categorised as fifth facial gestures, of which 800 were utilised for training and 200 for testing.

Data pre-processing and machine learning models

The FMCW radar was used for data collection, many parameters are important for target detection in radar systems such as Tx power, Carrier frequency, antenna gain, receiver sensitivity, target cross-section area, and receiver noise. To extract facial expression accurately, first detect the target location is needed. The target range in radar systems is defined by the delay between the transmitted and received echoes. Equation 1 shows the radar range equation:

$$R_{max} = 4\sqrt{\frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 K T_0 B F_n \frac{S}{N}}} \quad (1)$$

Where P_t is the transmitted power, G_t is the T_x antenna gain, G_r is the receiver antenna gain, λ is the wavelength, σ is the target cross-section area, K is Boltzmann's constant, T is the system temperature, B is the bandwidth, F is the receiver noise figure, and S/N is the signal-to-noise ratio^{32,33}. Firstly, we generated of the FMCW ramp which is the fundamental step in the operation of FMCW radar systems, enabling the measurement of target range based on the frequency difference between transmitted and received echoes. After that acquired the received echoes using an Analog-to-Digital Converter (ADC) with a sampling rate of 250 MSPS (Mega Samples Per Second) and applied signal processing techniques on collected samples such as low pass filtering, target extraction, and range calculation. Signal integration technique is applied for improving SNR to enhance the signal quality and increase the probability of detection. SNR was measured of the strength of the desired signal compared to the background noise level. Downsampling technique was used to reduce the sampling rate of a signal while retaining the essential information. We did downsampling to 10 MSPS. In the data pre-processing and machine learning (ML) approach, we utilised the widely used Scikit library, which provides comprehensive data analysis tools in Python³⁴. Additionally, we employed Pandas, a Python library, for parsing CSV files and converting them into data frames that can be further analyzed using Scikit-learn³⁵. Labels were assigned to the first column of the data frames. In the combined dataset, produced by merging the data frames of each sample, NaN (Not a Number) values may arise due to slight mismatches in the micro-Doppler signal. To handle these NaN values, we used the SimpleImputer function from Scikit-learn to replace them with the mean of each row. It is important to note that this data cleansing process does not alter the overall data patterns. The processed data was fed into various ML algorithms following the data cleansing step. The facial expression recognition system proposed in this study is evaluated using six different machine learning (ML) methods. The evaluation parameter for assessing the system's performance is the accuracy of correctly classifying various facial expressions. Each ML algorithm's accuracy is assessed independently using two approaches to ensure robust analysis: (i) k-fold cross-validation and (ii) train-test split. K-fold cross-validation is a widely adopted approach in ML testing, where the dataset is divided into k groups. In this experiment, we set k to 10, resulting in the dataset being divided into 10 groups or folds. Each group is then used as a test set while the remaining groups serve as training sets. This process is repeated k times, with each group acting as the test set once. The results obtained from each group of classifications collectively represent the performance of the ML algorithms on the entire dataset. In addition to k-fold cross-validation, the train-test split technique is employed. This technique involves dividing the dataset into training and testing subsets. The training data is used to train the ML models, enabling them to learn from the provided inputs and corresponding labels. The trained algorithms are then evaluated by making predictions on the testing data based on the learned patterns. In this study, 80% of each dataset is used for training, while the remaining 20% is used for testing. Furthermore, Fig. 4c lists the parameters used to configure the ML algorithms employed in the evaluation process.

Performance metrics for evaluating the classification model

In this study, the performance evaluation of ML models for facial expression dataset classification involves several metrics, including weighted average accuracy, precision, recall, f1-score, accuracy, and a 95% confidence interval (CI). The F1-score is a widely used metric in classification literature, serving as a measure of classification performance. It combines precision and recall, which are calculated using Eqs. (3) and (4), respectively. The

F1-score, calculated using Eq. (2), provides a comprehensive evaluation of the model's ability to balance both precision and recall in classification tasks. The overall accuracy of the combined dataset is calculated using 5 and verified the interval using 6. Where, the 95% asymptotic CI measures the statistical significance of experimental results. It represents the radius, with $n = 1000$ samples (20% of the dataset), and uses k as the number of standard deviations. The CI has a 95% probability of containing the true classification result. A value of $k = 1.96$ from the Gaussian distribution establishes this 95% confidence level.

$$F1 - Score = 2 \frac{Precision \cdot Recall}{Precision + Recall} \quad (2)$$

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \quad (3)$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \quad (4)$$

$$Accuracy = \frac{\sum (TP + TN)}{\sum (TP + FP + TN + FN)} \quad (5)$$

$$Interval = k \times \sqrt{\frac{Accuracy \times (1 - Accuracy)}{n}} \quad (6)$$

Results and discussion

This experimentation serves two purposes. In the first step, we introduced radar-based facial recognition, and in the next step, we compared the performance of various existing machine learning models such as Super Learner, Linear Discriminant Analysis, Random Forest, K Nearest Neighbour, Long Short-Term Memory, and Logistic Regression. We collected and analysed the performance of facial expression frameworks using different facial expression datasets such as “Neutral, Happy, Sad, Fair, and Surprise” from different genders. As a result, we performed experiments on Micro-Doppler signal data to evaluate the model's performance. The hyper-parameter settings for all models are listed in the Fig. 4c. All of the models on the dataset have been fine-tuned. Additionally, the training and testing sets were fixed throughout all studies. The percentages of the entire data in our training and testing sets are 80% and 20%, respectively. Figure 7a shows the outcomes of studies with various facial expression structures in terms of precision, recall, F1-score, and confidence interval. Figure 7b presents a bar graph illustrating accuracy, which aids in decision-making and comparisons. Figure 8 shows the confusion matrix of all proposed models on collected datasets. Overall, better outcomes were obtained for the combined and individual datasets using all models.

In the super learner algorithm, the combined dataset includes males and females. We got a high classification accuracy of 90% with precision, recall, and F1-score and accurate interval, which are shown in Fig. 8a. All the classes are correctly classified except “Fair” because 11% of expressions are similar to “Happy”.

Similarly, Linear Discriminant Analysis is well-performed on the combined dataset with 80% accuracy, precision, recall, f1-score and valid interval which are shown in Fig. 8b. All the classes are correctly classified except “Fair” which has been misclassified with “Happy”, “Sad”, and “Surprise” with a ratio of 0.08, 0.08, and 0.16.

Using Random Forest, the combined dataset includes males and females. We got a high classification accuracy of 85% with precision, recall, f1-score, and accurate interval which are shown in Fig. 8c. All the classes are correctly classified except “fair” and “surprise”. The “Fair” has similarities with “Happy” with a ratio of 0.16. Here again, “surprise” has similarities with “fair”, “happy”, “neutral”, and “sad” with ratios of 0.095, 0.048, 0.048, and 0.048.

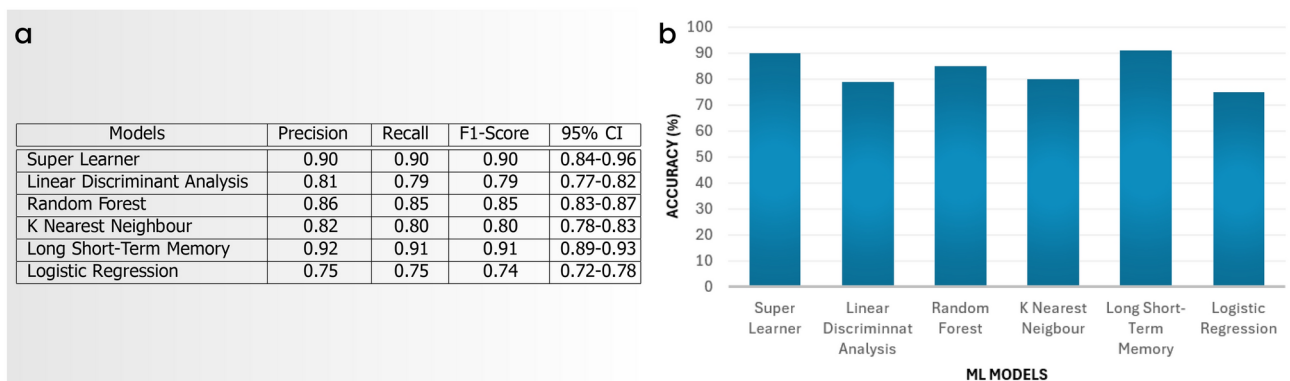


Fig. 7. (a) The evaluation of the ML models on the facial expression dataset involved measuring weighted average recall, weighted average precision, weighted average F1-score, accuracy, and determining a 95% confidence interval. (b) The bar graph shows accuracy.

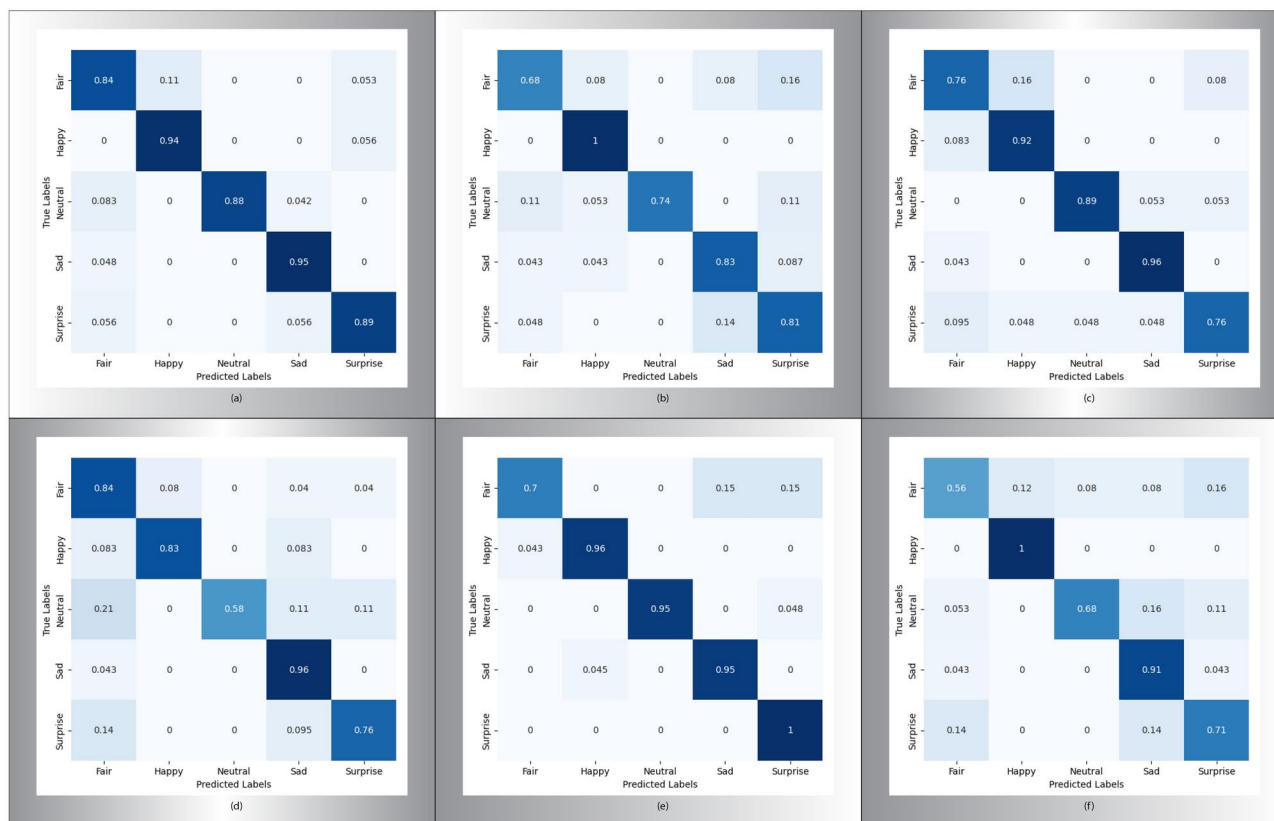


Fig. 8. The confusion matrix of well-known ML algorithms on the combined dataset. **(a)** Super Learner. **(b)** Linear discriminant analysis. **(c)** Random Forest. **(d)** K Nearest Neighbour. **(e)** Long Short-Term Memory. **(f)** Logistic Regression.

In the case of the K Nearest Neighbour algorithm, we got a high classification accuracy of 80%, precision, recall, f1-score, and interval, which are shown in Fig. 8d. Except for “surprise” all classes are correctly classified because it has similarity with “fair” and “sad” with a ratio of 0.14 and 0.095.

Using the Long Short-Term Memory algorithm on the combined dataset, we got high classification accuracy of 91%, precision, recall, f1-score, and interval, which are shown in Fig. 8e. All classes are correctly classified except “Fair” which has been misclassified with “sad” and “surprise” with ratios of 0.15 and 0.15.

Logistic Regression, the combined dataset includes males and females. We got a high classification accuracy of 75% with precision, recall, and F1-score and an accurate interval, which are shown in Fig. 8f. All the classes are correctly classified except “fair” because it has similarities with “happy”, “neutral”, “sad”, and “surprise” with ratios of 0.12, 0.08, 0.08, and 0.16.

Conclusion and future work

This paper presents a contactless and privacy-preserving facial recognition framework. The diverse dataset is taken from different users in the form of micro-doppler signals and fed into well-known machine learning models. The collected data consists of five different classes: neutral, happy, sad, fair, and surprise. The experiment included four participants, two male and two female, aged 20 to 40 years. The micro-Doppler data is fed into various machine learning models, including Super Learner, Linear Discriminant Analysis, Random Forest, K Nearest Neighbour, Long Short-Term Memory, and Logistic Regression. The face movements were mostly classified correctly, achieving a 100% accuracy rate. Among the models tested, the Long Short-Term Memory algorithm performed the best, with an overall accuracy of 91% for all five classes. Future research will focus on improving radar signal processing to enhance accuracy under various conditions. We plan to explore more advanced machine learning models to better differentiate between subtle facial expressions and increase the robustness of emotion recognition. Additionally, we will direct our research toward integrating our radar system with other sensing modalities, such as infrared or thermal imaging, to provide a more comprehensive understanding of facial expressions. We will also investigate ways to make the technology more adaptable to diverse age groups by incorporating a wider range of facial data into our training sets.

Data Availability

The datasets utilised in the current study are available from the corresponding author upon reasonable request at qammer.abbasi@glasgow.ac.uk.

Received: 28 April 2024; Accepted: 9 October 2024

Published online: 13 November 2024

References

- Chen, C.-H., Lee, I.-J. & Lin, L.-Y. Augmented reality-based video-modeling storybook of nonverbal facial cues for children with autism spectrum disorder to improve their perceptions and judgments of facial expressions and emotions. *Comput. Hum. Behav.* **55**, 477–485 (2016).
- Pise, A. A. et al. Methods for facial expression recognition with applications in challenging situations. *Comput. Intell. Neurosci.* **2022**, 9261438 (2022).
- Scherer, K. R., Banse, R. & Wallbott, H. G. Emotion inferences from vocal expression correlate across languages and cultures. *J. Cross-Cult. Psychol.* **32**, 76–92 (2001).
- Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M. & Pollak, S. D. Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. *Psychol. Sci. Public Interest* **20**, 1–68 (2019).
- Sato, W. & Yoshikawa, S. Spontaneous facial mimicry in response to dynamic facial expressions. *Cognition* **104**, 1–18 (2007).
- Filippini, C., Perpetuini, D., Cardone, D., Chiarelli, A. M. & Merla, A. Thermal infrared imaging-based affective computing and its application to facilitate human robot interaction: A review. *Appl. Sci.* **10**, 2924 (2020).
- O'Mahony, N. et al. Deep learning vs. traditional computer vision. In *Advances in Computer Vision: Proceedings of the 2019 Computer Vision Conference (CVC)* Vol 11 128–144 (Springer, 2020).
- Kim, J.-H., Kim, B.-G., Roy, P. P. & Jeong, D.-M. Efficient facial expression recognition algorithm based on hierarchical deep neural network structure. *IEEE Access* **7**, 41273–41285 (2019).
- Mollahosseini, A., Chan, D. & Mahoor, M. H. Going deeper in facial expression recognition using deep neural networks. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)* 1–10 (IEEE, 2016).
- Wu, Y., Zhang, L., Gu, Z., Lu, H. & Wan, S. Edge-ai-driven framework with efficient mobile network design for facial expression recognition. *ACM Trans. Embedded Comput. Syst.* **22**, 1–17 (2023).
- Komagal, E. & Yogameena, B. Ptz-camera-based facial expression analysis using faster r-cnn for student engagement recognition. In *Computer Vision and Machine Intelligence Paradigms for SDGs: Select Proceedings of ICRTAC-CVMIP 2021* 1–14 (Springer, 2023).
- Wienold, J. & Christoffersen, J. Evaluation methods and development of a new glare prediction model for daylight environments with the use of ccd cameras. *Energy Build.* **38**, 743–757 (2006).
- Yan, Z., Wu, Y., Zhang, Y. & Chen, X. Emoglass: an end-to-end ai-enabled wearable platform for enhancing self-awareness of emotional health. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* 1–19 (2022).
- Soufneyestani, M., Dowling, D. & Khan, A. Electroencephalography (eeg) technology applications and available devices. *Appl. Sci.* **10**, 7453 (2020).
- Kanjo, E., Al-Husain, L. & Chamberlain, A. Emotions in context: Examining pervasive affective sensing systems, applications, and analyses. *Pers. Ubiquitous Comput.* **19**, 1197–1212 (2015).
- Guk, K. et al. Evolution of wearable devices with real-time disease monitoring for personalized healthcare. *Nanomaterials* **9**, 813 (2019).
- Can, Y. S., Arnrich, B. & Ersoy, C. Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *J. Biomed. Inform.* **92**, 103139 (2019).
- Abdalla, M. H., Mustafa, K. H., Barbary, M., Refky, M. & El-Ghonami, M. R. Design and implementation of digital if waveform generation, acquisition, and receiver circuits for radar systems applications. In *2020 12th International Conference on Electrical Engineering (ICEENG)* 217–222. <https://doi.org/10.1109/ICEENG45378.2020.9171698> (2020).
- Dzedzickis, A., Kaklauskas, A. & Bucinskas, V. Human emotion recognition: Review of sensors and methods. *Sensors* **20**, 592 (2020).
- Shah, S. A. & Fioranelli, F. Rf sensing technologies for assisted daily living in healthcare: A comprehensive review. *IEEE Aerosp. Electron. Syst. Mag.* **34**, 26–44. <https://doi.org/10.1109/MAES.2019.2933971> (2019).
- Huynh, T.-P. & Haick, H. Autonomous flexible sensors for health monitoring. *Adv. Mater.* **30**, 1802337 (2018).
- Hu, W., Zhao, Z., Wang, Y., Zhang, H. & Lin, F. Noncontact accurate measurement of cardiopulmonary activity using a compact quadrature doppler radar sensor. *IEEE Trans. Biomed. Eng.* **61**, 725–735 (2013).
- Khan, A. N. et al. Deep learning framework for subject-independent emotion detection using wireless signals. *PLoS ONE* **16**, e0242946 (2021).
- Chen, Y., Ou, R., Li, Z. & Wu, K. Wiface: Facial expression recognition using wi-fi signals. *IEEE Trans. Mobile Comput.* **21**, 378–391 (2020).
- Li, B. & Lima, D. Facial expression recognition via resnet-50. *Int. J. Cogn. Comput. Eng.* **2**, 57–64 (2021).
- Singh, R. et al. Facial expression recognition in videos using hybrid cnn & convlstm. *Int. J. Inf. Technol.* **15**, 1819–1830 (2023).
- Uddin, M. Z. et al. A facial expression recognition system using robust face features from depth videos and deep learning. *Comput. Electr. Eng.* **63**, 114–125 (2017).
- Zhang, X., Zhang, Y., Shi, Z. & Gu, T. mmfer: Millimetre-wave radar based facial expression recognition for multimedia iot applications. In *Proceedings of the 29th Annual International Conference on Mobile Computing and Networking* 1–15 (2023).
- Gouveia, C. et al. Study on the usage feasibility of continuous-wave radar for emotion recognition. *Biomed. Signal Process. Control* **58**, 101835 (2020).
- Dang, X. et al. Wireless sensing technology combined with facial expression to realize multimodal emotion recognition. *Sensors* **23**, 338 (2022).
- Yin, H. et al. Let iot know you better: User identification and emotion recognition through millimeter-wave sensing. *IEEE Internet Things J.* **10**, 1149–1161 (2022).
- Skolnik, M. I. *Radar Handbook* 3rd edn. (McGraw-Hill Education, 2008).
- Mozeson, N. E. L. *Radar Signals* (Wiley, 2004).
- Hao, J. & Ho, T. K. Machine learning made easy: A review of scikit-learn package in python programming language. *J. Educ. Behav. Stat.* **44**, 348–361 (2019).
- Shi, S., Sigg, S., Chen, L. & Ji, Y. Accurate location tracking from csi-based passive device-free probabilistic fingerprinting. *IEEE Trans. Veh. Technol.* **67**, 5217–5230 (2018).

Acknowledgements

The support for this work was provided by grants EP/T021020/1 and EP/T021063/1 from the Engineering and Physical Sciences Research Council (EPSRC).

Author contributions

Conceptualisation, H.H., M.U., M.E., and Q.A.; Methodology, H.H., M.E., C.T., M.U., and Q.A.; Validation, H.H., M.U., M.E., J.K., N.N., Q.A., and M.I.; Formal Analysis, and H.H., A.Q., M.U.; Investigation, H.H., M.U.;

Resources, Q.A., and M.I.; Software, H.H., M.E., and J.L.K.; Data Creation, H.H., J.K.; Writing - Original Draft Preparation, H.H., and Q.A; Writing - Review & Editing, M.U., A.H., Q.A., and M.I.; Visualisation, H.H.; Supervision, Q.A., M.I., and M.U.; Project Administration, Q.A. and M.I.; Funding Acquisition, Q.A. and M.I. All authors have read and agreed to the published version of the manuscript.

Additional information

Correspondence and requests for materials should be addressed to H.H., or Q.H.A.

Competing Interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to Q.H.A.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2024