

# Driver Fatigue Detection Using Frequency-modulated Continuous Millimeter-wave Radar and Machine Learning with Feature Extraction

Shih-Pang Tseng,<sup>1\*</sup> I-Hui Hsiao,<sup>2</sup> and Jhing-Fa Wang<sup>2</sup>

<sup>1</sup>School of Software and Big Data, Changzhou University of Information Technology, Changzhou 213164, China

<sup>2</sup>Department of Electrical Engineering, National Cheng Kung University, Tainan 70101, Taiwan

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Distracted and fatigued driving is a major cause of traffic accidents worldwide, with statistics in Taiwan showing that 20% of annual accidents are attributed to these factors, ranking fatigue as the second leading cause. Drivers often experience reduced reaction times and impaired decision-making after continuous driving for 2–3 h, with post-meal and midnight driving further increasing drowsiness. Conventional fatigue detection methods, such as facial monitoring systems, can reduce accident rates by 10–20%, but they are limited by lighting conditions and raise privacy concerns. To solve these problems, a fatigue detection system is developed using frequency-modulated continuous-wave millimeter-wave radar. Using the Texas Instruments AWR1642boost development board, data were collected and analyzed through a multi-expert framework integrating four features: nodding, yawning, respiration, and heart rate. A support vector machine classifier was employed to enhance detection accuracy. The indoor simulation with 20 participants for 500 min of driving scenarios shows proof-of-concept feasibility, with an accuracy of 90.4%, a precision of 85.3%, and a recall of 88.2%. However, engine vibrations, cabin noise, road conditions, body positions, and driver fatigue must be considered in the simulation for further validation of the system. It is necessary to include larger, more diverse participant groups for on-road evaluations in complex environments.

## 1. Introduction

Fatigue driving is a persistent global safety challenge. It distracts attention, slows reaction time, and impairs judgment, all of which are critical for safe driving.<sup>(1–3)</sup> The World Health Organization attributes a significant share of the 1.3 million annual traffic deaths to driver fatigue.<sup>(4)</sup> In Taiwan, fatigue and distraction account for about 20% of car accidents, ranking as the second leading cause of crashes.<sup>(5)</sup> In the United States, fatigue contributes to 21% of fatal crashes,<sup>(6)</sup> whereas the Centers for Disease Control and Prevention of the United States reports

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\*Corresponding author: e-mail: [tsengshihpang@czcit.edu.cn](mailto:tsengshihpang@czcit.edu.cn)  
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that one in twenty-five adults reported falling asleep at the wheel within a single month.<sup>(5)</sup> These crashes harm drivers as well as passengers, cyclists, and pedestrians, amplifying the public safety burden.

Fatigue is a state of physical and mental exhaustion caused by prolonged wakefulness, insufficient sleep, or sustained cognitive demand.<sup>(3,7)</sup> It narrows attention, slows responses, and compromises decision-making.<sup>(8,9)</sup> However, drivers rarely assess their own fatigue accurately, and self-reporting is unreliable, especially since fatigue and sleepiness are difficult to distinguish.<sup>(10,11)</sup> Therefore, automated fatigue detection systems have been developed to sense physiological or behavioral signals of fatigue in real time to warn drivers before judgment deteriorates further and prompt corrective action. Such systems generate valuable data for understanding fatigue progression during real driving, supporting better prevention strategies.

Recent advances in millimeter-wave radar technology enable the accurate assessment of in-cabin driver monitoring and physiological state. The feasibility of extracting breathing patterns or heart-rate variability using continuous-wave or frequency-modulated continuous-wave (FMCW) radar setups has been verified in previous studies.<sup>(12)</sup> By tracking macro-level behavioral cues, such as head inclination or body fidgeting, simulated driving scenarios are also established.<sup>(12)</sup> However, existing radar-based driver state monitoring solutions require isolated single-modal features, such as thoracic vital signs or head posture, which degrade classification accuracy under drowsiness transitions where behavioral or physiological states vary. Few systems effectively integrate spatial segmentation algorithms to isolate simultaneous facial micro-motions, such as phase shifts during yawning, and thoracic cardiac signals without mutual interference.<sup>(13)</sup>

Two sensing methods are widely used in current fatigue detection systems: camera-based monitoring and wearable devices. Camera-based monitoring systems track eyelid closure, blink rate, and facial-muscle changes,<sup>(14,15)</sup> and are widely deployed. However, the systems are largely affected by ambient lighting, which reduces accuracy in darkness or glare and elevates fatigue risk. Error rates of the camera-based systems increase from 18% in daylight to 28% at night,<sup>(16)</sup> and privacy concerns further limit the driver acceptance of the systems.<sup>(15)</sup> In contrast, wearable devices are used to measure physiological signals such as electroencephalogram, heart rate, and electrodermal activity.<sup>(16,17)</sup> Although wearable devices are accurate in detecting fatigue, they require skin contact, which causes discomfort, irritation, and distraction, undermining their safety purpose.<sup>(18,19)</sup>

To overcome the limitations of the camera- and wearable-device-based fatigue detection systems, radar-based sensing has been introduced. Radar emits electromagnetic signals and reads reflections, enabling robust sensing in daylight, darkness, or glare. Radar operates independently of ambient light, preserves privacy, and requires no physical contact.<sup>(20,21)</sup> Owing to such properties, millimeter-wave (mmWave) radar offers advantages over the other systems. However, previous radar-based fatigue detection systems rely on a single vital sign or behavioral cue, such as respiration or head movement,<sup>(22,23)</sup> which demonstrates feasibility but lacks comprehensive feature integration, limiting accuracy.

This study was carried out to advance radar-based fatigue detection by fusing multiple complementary features, such as nodding, yawning, breathing, and heartbeat, into a single

noncontact sensing system. Using the Texas Instruments AWR1642BOOST 77 GHz FMCW radar development board,<sup>(21,23)</sup> we extracted these features from radar point-cloud and range-Doppler data. The developed system integrates the heterogeneous signals and classifies the driver's status with a support vector machine (SVM), achieving an accuracy of 90% in distinguishing driver fatigue. By combining behavioral and physiological features in one sensor, the system delivers precise information on the driver's status and improves accuracy compared with existing radar-based fatigue detection methods.<sup>(23)</sup>

## 2. Method

### 2.1 System overview and hardware configuration

The developed driver fatigue detection system processes FMCW radar signals through a multi-stage pipeline (Fig. 1). The system includes the Texas Instruments AWR1642BOOST evaluation board, which operates in the 76–81 GHz FMCW band. This frequency range provides high spatial resolution to distinguish targets spaced less than half a wavelength apart, maintaining compact antenna dimensions and low power consumption. The 77 GHz band offers finer range discrimination and improved sensitivity than the 24 GHz radar system in detecting subtle physiological motion.

Radar signals are transmitted through a universal asynchronous receiver-transmitter (UART) interface to the processing unit, where a multi-stage pipeline executes signal conditioning, region separation, feature extraction, and classification. In the signal preprocessing stage, noise reduction and range-Doppler transformation are performed to isolate meaningful reflections. In the body region, the separation module divides the radar point cloud into head and chest regions based on azimuth angles ( $-20$  to  $0^\circ$  for head,  $0$  to  $20^\circ$  for chest). In the feature extraction stage, four biomechanical and physiological indicators, including nodding, yawning, respiration, and heartbeat, are identified from the separated regions. These features are fused and classified by SVM to determine the driver's state as either fatigued or normal.

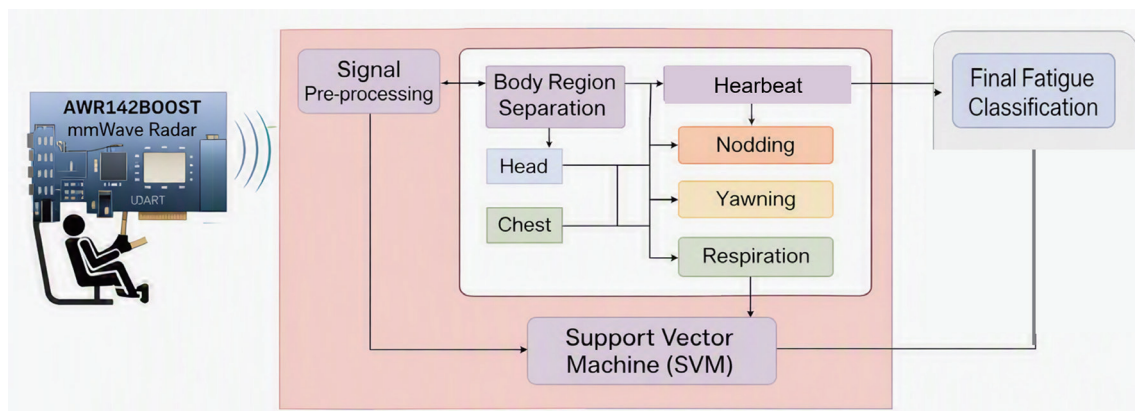


Fig. 1. (Color online) FMCW radar signal processing of driver fatigue detection systems in multi-stage pipeline.

The radar's operational configuration and important parameters used in this study are shown in Table 1. The radar operates with a start frequency of 77 GHz, a bandwidth of 4 GHz, and a frequency slope of 70 MHz/ $\mu$ s, achieving a frame rate of 4 frames per second (FPS). Two transmit (Tx)  $\times$  four receive (Rx) antenna arrays form an eight-channel virtual array, enabling fine-grained spatial resolution for in-cabin tracking within a 0.6–0.8 m range.

Table 2 shows the hardware specifications of the AWR1642BOOST radar. The system integrates a monolithic FMCW transceiver fabricated on a 45 nm radio frequency (RF) CMOS process, with a peak antenna gain exceeding 9 dBi across the operating band. The radar's processing subsystem combines a TI C674x Digital Signal Processor (600 MHz, Texas Instruments, USA) for FMCW signal processing and an ARM Cortex-R4F real-time microcontroller (200 MHz, ARM, USA) for radio control and tracking. The on-chip memory (1.5 MB) supports multi-level radar data buffering, while the UART, controller area

Table 1  
Parameters of operation of radar sensor used in this study.

| Parameter                              | Value           |
|----------------------------------------|-----------------|
| Software development kit (SDK) version | 3.6             |
| Start frequency                        | 77 GHz          |
| Bandwidth                              | 4 GHz           |
| Frequency slope                        | 70 MHz/ $\mu$ s |
| Frame rate                             | 4 FPS           |
| Number of Tx antennas                  | 2               |
| Number of Rx antennas                  | 4               |

Table 2  
Hardware specifications of radar used in this study (TI AWR1642BOOST, Texas Instruments, USA).

| Category                    | Component                | Specification                                                                           |
|-----------------------------|--------------------------|-----------------------------------------------------------------------------------------|
| RF transceiver              | Architecture             | Monolithic FMCW transceiver (45 nm radio frequency CMOS)                                |
|                             | Frequency range          | 76–81 GHz (4 GHz continuous bandwidth)                                                  |
|                             | Antenna array            | 2 Tx, 4 Rx channels                                                                     |
|                             | Antenna peak gain        | >9 dBi across 76–81 GHz                                                                 |
|                             | Tx power                 | 12 dBm                                                                                  |
|                             | Rx noise figure          | 14 dB (76–77 GHz), 15 dB (77–81 GHz)                                                    |
| Processing subsystem        | Digital signal processor | TI C674x digital signal processor (DSP) at 600 MHz (FMCW processing)                    |
|                             | Microcontroller          | ARM <sup>®</sup> Cortex <sup>®</sup> -R4F at 200 MHz (radio control and tracking)       |
|                             | On-chip memory           | 1.5 MB of random access memory (RAM) (level 3 radar data memory and DSP levels 1 and 2) |
|                             | Max adc sampling rate    | 12.5 Msps                                                                               |
| Interfaces and power supply | Data interfaces          | UART (USB-to-PC), CAN/CAN-flexible data rate, SPI, LVDS                                 |
|                             | Power supply             | 5 V DC ( $\geq$ 2.5 A)                                                                  |

network (CAN), serial peripheral interface (SPI), and low-voltage differential signaling (LVDS) interfaces enable flexible data communication. The radar operates on a 5 V DC power supply ( $\geq 2.5$  A), ensuring stable performance during continuous acquisition.

Table 3 shows the experimental parameter settings configured through the SDK 3.6 command-line interface. The radar's fast Fourier transform (FFT) window length (30 frames, 7.5 s) and stride (8 frames, 2.0 s) enable real-time frequency-domain analyses of respiration and heartbeat signals. These settings were selected to balance temporal resolution and computational efficiency and to continuously monitor signals without loss. The azimuth field of view ( $-20$  to  $+20^\circ$ ) ensures the full coverage of the driver's upper body while minimizing interference from surrounding cabin structures. The combination of high-frequency FMCW radar, multi-expert signal processing, and machine-learning classification provides a contactless, light-independent, and privacy-preserving solution for real-time driver monitoring.

## 2.2 Signal processing and feature extraction

The radar transmits raw reflected signals as type-length-value structures over the UART interface to a host computer. Occasional high-amplitude pulse noise distorts single frames. To isolate biological motion from transient interference, smoothing filters are applied to suppress noise and preserve high-amplitude head-tilt shifts. Frames exhibiting pervasive pulse noise across all range bins are discarded to maintain signal integrity.

The accurate tracking of driver body parts requires the spatial segmentation of the radar point cloud. Therefore, the developed system isolates the target into two distinct regions using the estimated distance ( $d$ ) and arrival angle ( $\theta$ ) (Fig. 2). The head region is defined by distance  $d_{\text{head}}$  and angle  $\theta_{\text{head}}$  (ranging from  $-20$  to  $0^\circ$ ), whereas the chest region is defined by distance  $d_{\text{chest}}$  and angle  $\theta_{\text{chest}}$  (ranging from  $0$  to  $20^\circ$ ). The radar sensor is mounted at a distance of 0.6–0.8 m from the driver. Centering the radar beam on the upper body aligns the target area with the peak antenna gain near  $0^\circ$  azimuth (Fig. 3) to maximize signal quality and measurement accuracy across both body segments.

From these separated signals, the system extracts four biological features: nodding, yawning, respiration rate, and heart rate. These features form a multi-modal vector processed by an SVM classifier to capture nonlinear decision boundaries between fatigued and alert states. Head

Table 3  
Experimental parameter settings configured using command line interface/SDK 3.6.

| Parameter             | Value                      | Description                                                                      |
|-----------------------|----------------------------|----------------------------------------------------------------------------------|
| Start frequency       | 77 GHz                     | Base operating frequency                                                         |
| Bandwidth             | 4 GHz                      | Frequency sweep range (77–81 GHz)                                                |
| Frequency slope       | 70 MHz/ $\mu$ s            | Chirp frequency modulation rate                                                  |
| Frame rate            | 4 FPS                      | Update interval (250 ms per frame)                                               |
| Tx/Rx active channel  | 2 Tx/4 Rx                  | Virtual array configuration ( $2 \times 4 = 8$ channels)                         |
| Target distance range | 0.6–0.8 m                  | In-cabin driver tracking range                                                   |
| Azimuth field of view | $-20^\circ$ to $+20^\circ$ | Divided into head ( $-20$ to $0^\circ$ ) and chest ( $0$ to $20^\circ$ ) regions |
| FFT window length     | 30 frames (7.5 s)          | Time-series length for heart rate frequency analysis                             |
| FFT window stride     | 8 frames (2.0 s)           | Overlap sliding interval for real-time updating                                  |

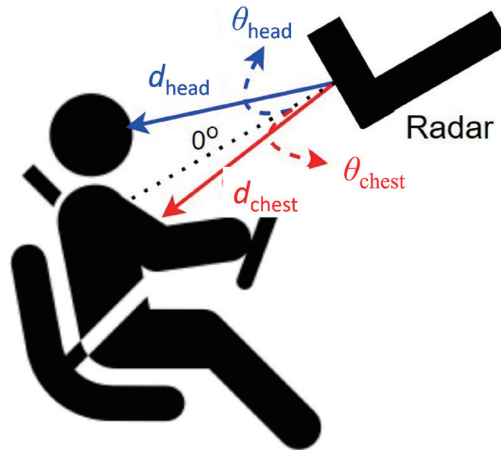


Fig. 2. (Color online) Spatial segmentation of driver body regions based on target range ( $d$ ) and arrival angle ( $\theta$ ).

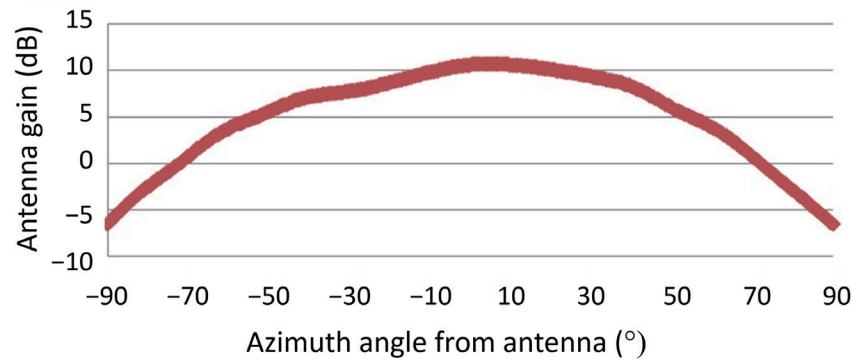


Fig. 3. (Color online) Azimuth radiation pattern of AWR1642BOOST FMCW radar sensor, showing antenna gain (dB) as function of azimuth angle with peak performance centered near 0°.<sup>(23)</sup>

nodding is detected by analyzing amplitude and phase components from the azimuth static heatmap of the head region. Forward tilting alters the distance and angle relative to the radar, and deviations exceeding 20° indicate nodding. Yawning produces subtle phase variations that amplitude alone cannot resolve. By measuring phase differences between mouth closure and wide opening in the lower facial point cloud, yawning events are identified. Respiration is tracked by monitoring cyclical phase oscillations in the chest region caused by inhalation and exhalation. Heartbeat detection relies on sub-millimeter chest displacement induced by cardiac contractions, visible as high-frequency phase fluctuations. An FFT analysis was conducted on 30-frame windows (7.5 s) with an 8-frame stride (2 s), updating heart-rate estimates every 2 s. Frequencies between 1.0 and 1.7 Hz (60–100 beats per min) are isolated, and an outlier filter removes spurious readings.

### 2.3 Experiment

The experiments were conducted using the Texas Instruments AWR1642BOOST radar evaluation board connected to a host computer equipped with an Intel(R) i5-11400 @ 2.60 GHz CPU, an NVIDIA RTX 3060 graphics processing unit, and 64 GB of RAM. Python was used for signal processing, feature extraction, and classification. The experimental setup is shown in Fig. 4. A front-facing monitor displayed driving simulation videos to replicate the driver's perspective, and a secondary monitor on the right presented real-time detection results. The radar module was positioned in front of the participant, directed toward the upper body to capture head and chest micro-motions. Participants interacted with the simulation using a keyboard and mouse, ensuring realistic engagement with the driving environment.

Twenty participants were recruited to evaluate the system's performance. Each participant completed a 5 min session, during which radar-derived fatigue features were compared against ground-truth measurements. The mean absolute error for each feature was calculated over 1 min intervals. Ground-truth heart rate values were obtained using the Fudakang Automatic Arm-Type Electrical Blood Pressure Meter FT-C12B, a cuff-based contact device certified by the Taiwan Ministry of Health and Welfare (Registration No. 000979).

In 500 min of testing with 20 participants, the system yielded the following outcomes: 157 instances where fatigue features were correctly detected and classified, 27 false positives, where no fatigue features were present but were flagged as abnormal, 21 false negatives, where fatigue features were present but misclassified as normal, and 295 true negatives, where no fatigue features were present and correctly classified as normal. These results confirm the system's ability to reliably distinguish fatigued from alert states under realistic experimental conditions.

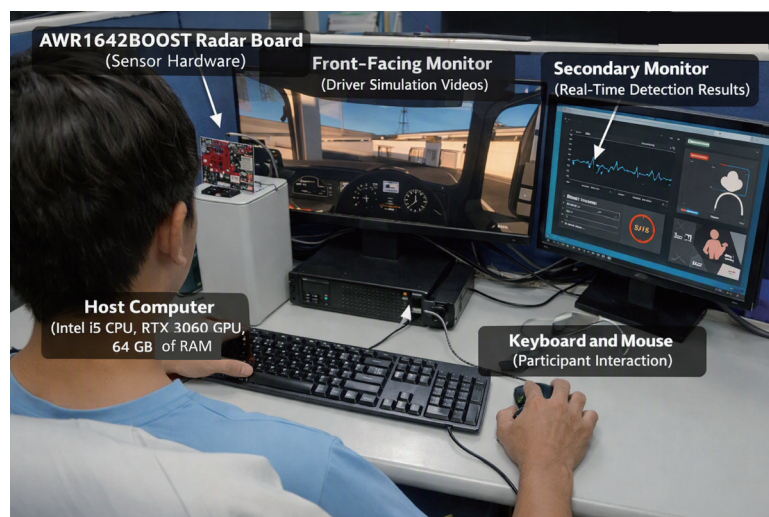


Fig. 4. (Color online) Experimental setup with radar device, host computer, and dual-screen configuration.

## 2.4 Performance evaluation

To evaluate model performance and examine nonlinear feature interactions, the results of four machine learning and deep learning algorithms were compared: SVM with radial basis function (RBF) kernel, random forest (RF, ensemble classifier with 100 decision trees), 1D convolutional neural network (1D-CNN), and long short-term memory (LSTM) network.<sup>(24)</sup> A fivefold cross-validation scheme was employed across the 500 min dataset to prevent data leakage and evaluate generalization capability. In each fold, the same ratio of fatigue to alert instances was used [178 fatigue instances to 322 non-fatigue/alert instances, which corresponds to 35.6% fatigue state and 64.4% alert state (in a 1:1.81 class ratio)]. Classification accuracy, precision, recall, and  $F_1$ -score were calculated for all five folds. These metrics were calculated from the confusion matrix comprising true positives ( $TP$ ), true negatives ( $TN$ ), false positives ( $FP$ ), and false negatives ( $FN$ ).

Classification accuracy is the proportion of correctly classified samples among all evaluated samples and is expressed as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} . \quad (1)$$

Precision represents the proportion of correctly identified fatigue events among all samples predicted as fatigue.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall, also referred to as sensitivity, is the proportion of actual fatigue events correctly detected by the model.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$F_1$ -score is the harmonic mean of precision and recall and provides a balanced assessment of classification performance.

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Higher values of accuracy, precision, recall, and  $F_1$ -score indicate higher fatigue classification performance.

3. Results

Radar-based feature extraction was conducted to compare the results with ground-truth measurements recorded every minute for each participant. Table 4 shows the mean absolute error (*MAE*) of the five fatigue-related features. Respiration showed the highest tracking accuracy (3.75% *MAE*), confirming the radar’s sensitivity to chest-wall motion. Yawning exhibited the highest error (8.72%) due to smaller reflective surfaces and subtle mouth-region phase changes.

The extracted features corresponded well with the results shown in Figs. 5–8. Figure 5 shows the time-amplitude plot of the head, where amplitude fluctuations mark forward head tilts exceeding 20°, confirming nodding detection. In the figure, radar signals vary over time as the driver’s head moves, providing a visual representation of fatigue-related behavior. On the *y*-axis, range bin index represents the radar’s spatial sampling points corresponding to the head region. The color scale indicates signal amplitude intensity, with darker tones (purple/blue) showing low reflection strength and brighter tones (green/yellow) showing high amplitude returns. The red box marks a period between roughly 30 and 40 s, where amplitude values increase sharply. This

Table 4  
*MAE* of extracted fatigue features.

| Feature     | <i>MAE</i> (%) |
|-------------|----------------|
| Nodding     | 5.45           |
| Yawning     | 8.72           |
| Blinking    | 8.38           |
| Respiration | 3.75           |
| Heart rate  | 6.04           |

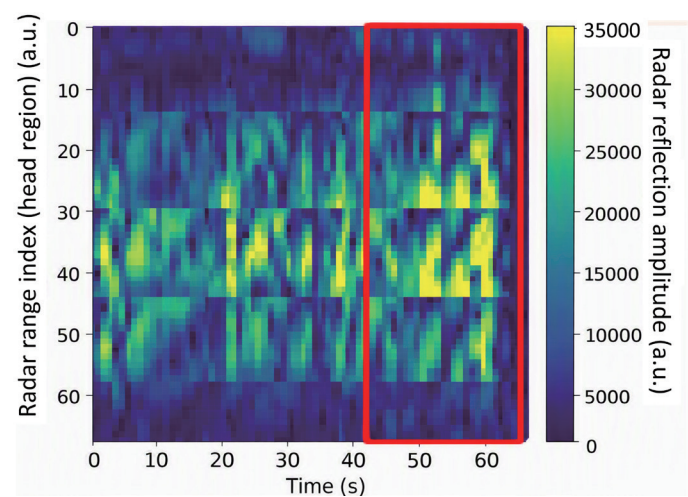


Fig. 5. (Color online) Time-amplitude heatmap of the head region. Color scale represents radar reflection amplitude, where brighter regions indicate stronger signal returns. The highlighted region corresponds to nodding events, characterized by pronounced amplitude variations relative to the surrounding steady-state head posture.

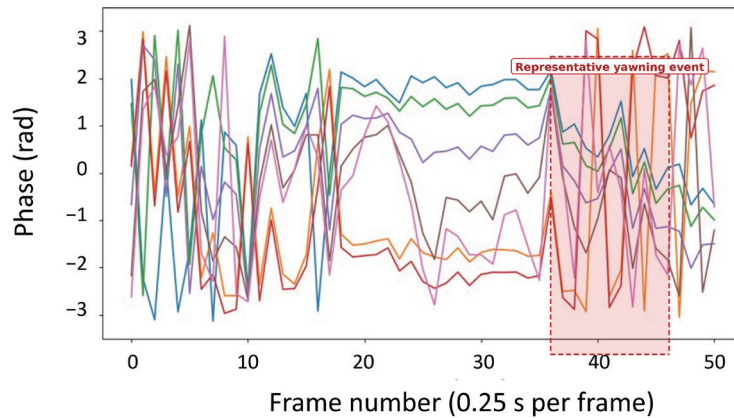


Fig. 6. (Color online) Time-phase plot of the mouth region. Each colored line represents radar phase variation for seven participants. The red-shaded region indicates a representative yawning event, where large mouth opening produces pronounced phase deviations relative to the normal mouth-closure state.

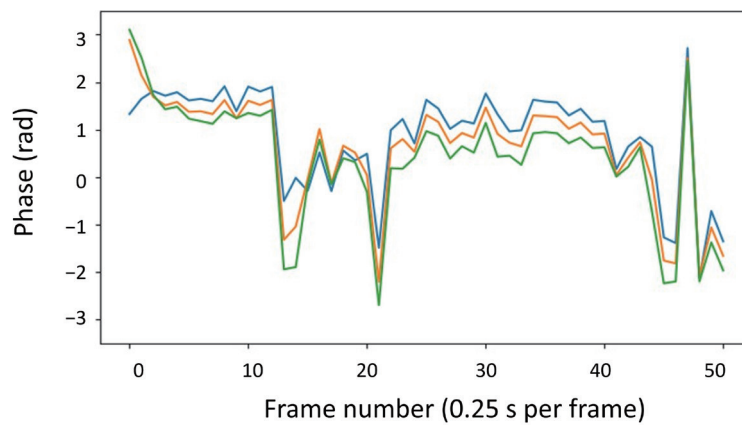


Fig. 7. (Color online) Time-phase plot of chest region. Each colored line represents radar phase variation for one participant during respiration monitoring. The oscillatory patterns correspond to inhalation and exhalation cycles, demonstrating the radar's ability to track respiration noninvasively across multiple subjects.

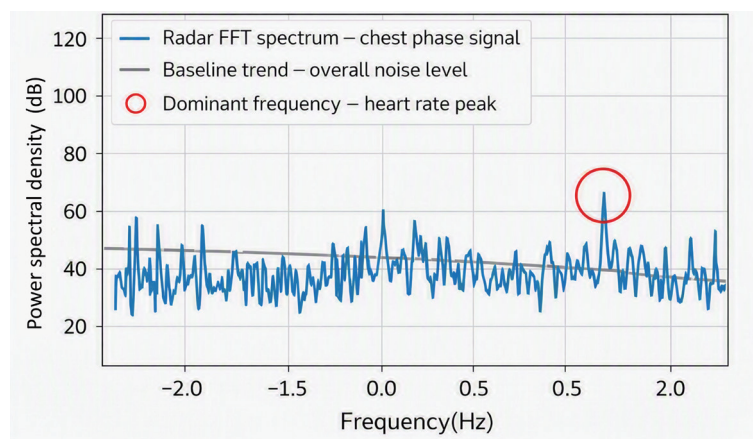


Fig. 8. (Color online) FFT spectrum of chest phase signals.

region corresponds to head-tilt motion, the driver's head moving forward and downward, typical of a nodding event. The radar detects this as changes in reflected signal strength and distance, confirming the system's ability to identify fatigue-related head movements. Figure 5 shows the time-amplitude heatmap of the head region obtained from the FMCW radar. The  $x$ -axis represents time (s) and the  $y$ -axis represents the head-region radar range index corresponding to discrete distance intervals between the radar and the driver's head. The color scale indicates radar reflection amplitude, where brighter colors denote stronger signal returns. The highlighted region between 42 and 65 s corresponds to a representative nodding event, in which pronounced amplitude variations are observed. In contrast, relatively stable low-amplitude patterns are present during periods of normal head posture. This distinction demonstrates the radar's ability to differentiate dynamic head motion from static posture and supports the nodding detection performance reported in Table 4.

Figure 6 shows the time-phase plot of the mouth and phase shifts between mouth closure and opening during yawning. The  $x$ -axis (frame number, 0.25 s per frame) represents time progression and the  $y$ -axis shows the radar signal's phase shift. During normal mouth closure, the phase remains relatively stable. When yawning occurs, the mouth opens widely, changing the distance between the radar and the reflecting surface. This movement produces a distinct phase deviation, visible as oscillations or spikes in the plot. The radar system sets a threshold for phase change to classify yawning events. Because amplitude alone cannot resolve small mouth movements, phase analysis provides a more sensitive measure of fatigue-related facial motion. Figure 6 shows that phase-based detection captures fine facial movements that traditional amplitude tracking would miss, confirming the radar's precision in identifying yawning, which is an essential fatigue indicator.

Figure 7 shows cyclical phase oscillations in the chest region caused by respiration cycles, and Fig. 8 presents the FFT spectrum of chest motion, highlighting a dominant frequency near 1.0 Hz (60 beats per minute). In Fig. 7, the  $x$ -axis (frame number, 0.25 s per frame) represents time and the  $y$ -axis (Phase, rad) shows radar phase changes. Each oscillation corresponds to one respiration cycle: inhalation followed by exhalation. The smooth, periodic waveform indicates stable breathing, whereas irregular or flattened cycles would suggest fatigue or drowsiness. The radar's high sensitivity enables the detection of sub-millimeter chest displacement, allowing accurate respiration tracking even through clothing. The periodicity observed in Fig. 7 indicates the radar's ability to monitor respiration noninvasively, achieving the lowest mean absolute error (3.75%) among all extracted features (Table 4).

The FFT analysis was conducted to convert chest phase signals into the frequency domain (Fig. 8). In Fig. 8, the  $x$ -axis represents frequency (Hz) and the  $y$ -axis represents power spectral density (dB). The blue line shows the radar FFT spectrum, the gray straight line indicates the baseline noise level, and the red circle highlights the dominant frequency peak near 1.0 Hz, corresponding to a normal adult heart rate of ~60 beats per minute. A distinct spectral peak near 1.0 Hz corresponds to a normal resting heart rate of ~60 beats per minute. By isolating frequencies between 1.0 and 1.7 Hz (60–100 bpm), the system reliably estimates heart rate while filtering out respiration harmonics and noise. Figures 7 and 8 show the radar's capability to extract respiration and heartbeat signals from subtle chest movements, confirming its effectiveness in physiological fatigue monitoring.

The results show the radar's ability to capture both macro-motions (nodding, yawning) and micro-motions (respiration, heartbeat) with high temporal precision. The results also show that the phase-based approach effectively distinguishes fatigue-related physiological signals from noise. The radar's frequency-domain analysis further confirms that the extracted heart-rate frequencies fall within the normal physiological range (1.0–1.7 Hz), validating the system's biomedical reliability. Moreover, the azimuth-based region separation ( $-20$  to  $0^\circ$  for head,  $0$  to  $20^\circ$  for chest) improved signal isolation and reduced cross-interference between facial and thoracic reflections. This spatial segmentation enhanced the clarity of feature extraction, particularly for respiration and heartbeat signals, which are easily masked by head movement in unsegmented radar data.

We also evaluated the model using a total evaluation time of 500 minutes from 20 participants. The dataset comprised 178 true fatigue events and 322 nonfatigue states. Table 5 shows the resulting confusion matrix. The developed model shows an overall classification accuracy of 90.4%  $[(157+295)/500]$ , a precision of 85.3%  $[157/(157+27)]$ , and a recall of 88.2%  $[157/(157+21)]$ .

The higher detection accuracy for head nodding (94.55%) and eye blinking (91.62%) of the FMCW radar system than of the representative camera-based models prevents susceptibility to illumination variations and privacy concerns associated with optical monitoring systems (Table 6).<sup>(14,15)</sup> For physiological monitoring, the system showed accuracies of 96.25% for respiration and 93.94% accuracy for heartbeat estimation, demonstrating performance comparable to or exceeding that of the existing Wi-Fi-, RF identification (RFID)-, and radar-

Table 5  
Confusion matrix for driver fatigue detection.

| Ground truth | Model prediction |                 |
|--------------|------------------|-----------------|
|              | Positives        | Negatives       |
| Positives    | <i>TP</i> (157)  | <i>FN</i> (21)  |
| Negatives    | <i>FP</i> (27)   | <i>TN</i> (295) |

Table 6  
Performance comparison of FMCW radar system with existing driver fatigue detection methods.

| Target feature  | Sensing method             | Performance                       | Model developed in this study    |
|-----------------|----------------------------|-----------------------------------|----------------------------------|
| Nodding         | Camera <sup>(15)</sup>     | 89.42% accuracy                   | 94.55% accuracy                  |
| Yawning         | Camera <sup>(14,15)</sup>  | 84.63–94.31% accuracy             | 91.28% accuracy                  |
| Blinking        | Camera <sup>(14)</sup>     | 88.41% accuracy                   | 91.62% accuracy                  |
|                 | Wi-Fi <sup>(14)</sup>      | 0.31 beats per minute (BPM) error |                                  |
| Respiration     | RFID <sup>(17)</sup>       | 0.54 BPM error                    | 96.25% accuracy (0.33 BPM error) |
|                 | FMCW <sup>(20)</sup>       | 94.00% accuracy                   |                                  |
|                 | Radar <sup>(21)</sup>      | 88.54% (5.28 BPM error)           |                                  |
| Heartbeat       | FMCW <sup>(20)</sup>       | 80.00% accuracy                   | 93.94% accuracy (4.63 BPM error) |
| Overall fatigue | FMCW radar <sup>(22)</sup> | 85.00% accuracy                   | 90.40% accuracy                  |

based techniques.<sup>(21,22)</sup> By integrating indicators of head posture, mouth-opening dynamics, respiration, and cardiac activity, the system increased the overall fatigue detection accuracy to 90.40%, representing a 5.4% improvement over previously reported single-mode FMCW radar systems.<sup>(23)</sup> These results indicate the effectiveness of multi-feature fusion in driver fatigue detection performance in a privacy-preserving, noncontact sensing environment.

Table 7 shows the fivefold cross-validation performance of the SVM, RF, 1D-CNN, and LSTM models using the extracted multi-feature dataset. The SVM model showed the highest performance, yielding an accuracy of 90.40%, a precision of 85.33%, a recall of 88.20%, and an  $F_1$ -score of 86.74%. Random forest presented an accuracy of 88.60%, whereas 1D-CNN and LSTM showed accuracies of 84.20 and 83.00%, respectively. This performance difference is attributed to the limited dataset size and the use of pre-extracted feature vectors, which generally favor traditional machine-learning approaches over data-intensive deep-learning models.

To assess the robustness of the results, 95% confidence intervals (CIs) were estimated using bootstrap resampling ( $B = 1000$ ). The proposed SVM model achieved an accuracy of 90.40% (95% CI of 87.80–92.80%), a precision of 85.33% (95% CI of 80.10–90.20%), and a recall of 88.20% (95% CI of 83.40–92.60%). Paired two-tailed  $t$ -tests were conducted on the fivefold cross-validation accuracy. The results showed that the SVM model outperformed the 1D-CNN ( $t = 3.82$ ,  $p = 0.018$ ) and LSTM ( $t = 4.41$ ,  $p = 0.011$ ) models, presenting an advantage over random forest ( $t = 2.78$ ,  $p = 0.049$ ). These results indicate that the SVM classifier is reliable and generalizable for driver fatigue detection using the dataset used in this study.

When domain-specific signal processing is used to translate raw mmWave point clouds into structured, multi-modal features, including posture, facial micro-motion, and vital signs, classical machine learning classifiers, such as SVM with an RBF kernel, outperform 1D-CNN and LSTM. This result shows that structured biological feature vectors reduce input dimensionality, and SVM effectively models nonlinear cross-feature dependencies without overfitting, which affects deep neural networks on moderate sample sizes. The performance of SVM indicates the feasibility of real-time, low-latency execution on embedded automotive microcontrollers without requiring dedicated graphics processing unit acceleration.

Table 7  
Fivefold cross-validation performance comparison of different classification models.

| Model               | Architecture<br>(hyperparameters)                                                                  | Accuracy (%)<br>[95% CI] | Precision (%)<br>[95% CI] | Recall (%)<br>[95% CI]  | $p$ -value<br>(compared<br>with SVM) | $F_1$ -score<br>(%) |
|---------------------|----------------------------------------------------------------------------------------------------|--------------------------|---------------------------|-------------------------|--------------------------------------|---------------------|
| SVM<br>(this study) | RBF kernel<br>(regularization parameter<br>$C = 1.0$ ,<br>kernel scale $\gamma = \text{'scale'}$ ) | 90.40<br>[87.80, 92.80]  | 85.33<br>[80.10, 90.20]   | 88.20<br>[83.40, 92.60] | —                                    | 86.74               |
| Random<br>forest    | 100 trees,<br>maximum depth = 10                                                                   | 88.60<br>[85.80, 91.20]  | 83.15<br>[77.60, 88.40]   | 86.52<br>[81.20, 91.00] | 0.049                                | 84.8                |
| 1D-CNN              | 2 1D convolutional<br>+ max pooling<br>+ fully connected<br>(FC) layers                            | 84.20<br>[81.00, 87.20]  | 78.40<br>[72.30, 84.10]   | 81.10<br>[75.20, 86.50] | 0.018                                | 79.73               |
| LSTM                | 2 LSTM layers (64 units)<br>+ FC                                                                   | 83.00<br>[79.60, 86.20]  | 76.90<br>[70.80, 82.50]   | 80.34<br>[74.40, 85.80] | 0.011                                | 78.58               |

## 4. Discussion

### 4.1 Performance evaluation and implications

The developed FMCW radar system accurately captures macro-motions, such as nodding and yawning, and micro-motions, including respiration and heartbeat, with high temporal precision. The ability to detect these distinct motion scales presents the radar's versatility in monitoring behavioral and physiological indicators of fatigue. The phase-based approach of the developed system is effective in distinguishing fatigue-related signals from environmental noise, ensuring reliable detection even under conditions of minor posture changes or ambient interference. This capability is essential for real-world applications, where drivers exhibit natural variability in movement and external disturbances are unavoidable.

The frequency-domain analysis result validated the radar's biomedical reliability. The extracted heart-rate frequencies consistently fell within the normal physiological range of 1.0–1.7 Hz, indicating that the radar can serve as a noncontact alternative to conventional biomedical sensors. This has important implications for sensor technology development, as radar systems can achieve medical-grade accuracy without requiring physical contact or wearable devices. Such noninvasive monitoring can be integrated into vehicle cabins, smart homes, and healthcare environments, enabling the continuous observation of vital signs while maintaining user comfort and privacy. Spatial segmentation through azimuth-based region separation ( $-20$  to  $0^\circ$  for the head and  $0$  to  $20^\circ$  for the chest) significantly enhanced signal isolation and reduced cross-interference between facial and thoracic reflections. This methodological refinement enhances the clarity of feature extraction for respiration and heartbeat signals that are often masked by head movement in unsegmented radar data. The approach shows how angular domain processing can be leveraged to increase radar precision in multi-region sensing, providing a foundation for future systems capable of tracking multiple body parts or individuals simultaneously.

The classification results, an overall accuracy of 90.4%, a precision of 85.3%, and a recall of 88.2%, indicate that the multi-feature SVM classifier performs robustly across diverse participants and conditions. The high recall rate suggests that fatigue events are detected reliably and the precision score reflects the system's ability to minimize false alarms. These outcomes show the feasibility of real-time fatigue monitoring using radar signals, supporting its potential integration into advanced driver-assistance systems. The model's stability over 500 min of evaluation also highlights its generalization capability, an essential attribute for deployment in practical environments. The results of statistical significance testing showed that the observed accuracy gains were mathematically sound and reproducible.<sup>(25)</sup> The 95% *CI* [87.80%, 92.80%] for accuracy indicates the model's stability across various continuous driving segments. The SVM classifier significantly outperformed 1D-CNN and LSTM, suppressing an artifact of random sample variation.<sup>(25)</sup>

Comparative analysis results with existing sensing technologies show the advantages of the proposed radar system. The developed model achieves accuracies of 94.55% in nodding and 91.62% in blinking, outperforming optical methods that depend on lighting conditions and raise

privacy concerns. Similarly, respiration and heartbeat detection reach accuracies of 96.25 and 93.94%, respectively, surpassing Wi-Fi, RFID, and earlier radar benchmarks. The overall fatigue detection accuracy improved by 5.4% compared with single-mode FMCW radar systems, demonstrating the effectiveness of multi-modal feature fusion. By integrating head posture, mouth opening, respiration, and cardiac spectrum analysis, the system provides a comprehensive assessment of driver fatigue that combines behavioral and physiological dimensions.

The precision and reliability of FMCW radar sensing show how radar can transition from traditional object detection to human-state monitoring, bridging the gap between mechanical sensing and biomedical intelligence. Its noncontact design eliminates the need for intrusive sensors, offering a privacy-preserving solution for continuous health and attentiveness monitoring. The integration of spatial segmentation and phase-domain analysis establishes a framework for future radar systems capable of multi-parameter tracking, adaptive calibration, and real-time data fusion with artificial intelligence algorithms.

FMCW radar serves as a cornerstone for next-generation sensing platforms that unify safety, health, and human-machine interaction. The developed system enhances fatigue detection accuracy and shows how radar technology can evolve into a versatile tool for physiological monitoring and intelligent environmental awareness. These results mark a meaningful step toward the convergence of automotive sensing and biomedical engineering, positioning radar as a key enabler of safer and more responsive human-centric systems.

FMCW radar technology in fatigue detection needs to include multi-modal integration, where radar is combined with other sensing modalities such as cameras, lidar, or ultrasonic sensors to create a more comprehensive system. By leveraging the robustness of radar in adverse weather conditions alongside the high-resolution imaging capability of lidar, a more precise perception framework can be constructed. By utilizing FMCW radar data in advanced algorithms, recognition, classification, and tracking accuracy can be enhanced, which requires the development of larger radar-specific datasets. It is necessary to expand databases and train models on large-scale radar measurements to enable the accurate differentiation of objects, the prediction of behavior, and decision-making based on radar signals. Through such advancement, the potential of FMCW radar for driver fatigue detection can be enhanced for next-generation intelligent sensing systems.

The performance comparison of different models shows that SVM and RF outperform 1D-CNN and LSTM on the dataset used in this study. Because the multi-expert feature extraction method used in this study enables the translation of continuous radar point clouds into compact, structured biomechanical vectors (nodding angle, yawning phase shift, respiration frequency, and cardiac spectrum), the classification task adopts tabular decision boundaries rather than raw signal representation learning. Under these conditions, the nonlinear RBF kernel of the SVM accurately captures complex interactions among biological features without suffering from over-parameterization.<sup>(24)</sup> In contrast, 1D-CNN and LSTM operate on massive raw time-series inputs. For the size of 20 participants over 500 min operation, deep networks tend to overfit the training folds during fivefold cross-validation. Despite this, since larger radar point-cloud datasets become available, end-to-end deep learning on raw range-Doppler maps is a promising method for multi-modal feature learning.<sup>(24)</sup>

## 4.2 Application to automotive

For integration into vehicles, the sensor physical layout, power budget, and manufacturing costs must be tailored to automotive original equipment manufacturer standards.<sup>(G3)</sup> Although the distance of 0.6–0.8 m to the subject for the optimal signal acquisition of the radar sensor was used in the experiment, the distance between the instrument cluster behind the steering wheel or the overhead rear-view mirror console and a driver can be much shorter. By mounting the radar in the rear-view mirror assembly (0.8–1.1 m), an unobstructed line of sight to the driver's upper chest and head can be obtained, preserving cabin ergonomics and avoiding steering wheel occlusion. Since mm-wave electromagnetic signals penetrate standard radio-frequency-transparent automotive plastics, hidden packaging can be used.<sup>(26)</sup> Monolithic radio-frequency complementary metal-oxide-semiconductor radar transceivers can be used to operate on a 5 V DC supply with a power draw of approximately 1.5–2.5 W, making them energy-efficient and powered by a standard automotive 12-V power supply. Unlike camera-based driver monitoring systems that demand high-power infrared LED illumination bars and expensive image processing units, the single-chip FMCW radar provides a highly cost-effective, energy-efficient, and nonintrusive solution for continuous driver fatigue monitoring.

Although FMCW radar feature extraction and fatigue classification were focused on in this study, an effective alert system is essential to enable actionable driver intervention. To avoid driver habituation or sudden distraction, a multi-stage, multi-modal alert framework is used. The system can be integrated with a stage-one warning system included in the vehicle's instrument cluster. If the classification model registers sustained fatigue signals, the system can issue a warning, triggering multi-sensory feedback, including high-priority auditory warnings, seat or steering wheel haptic vibrations, and the automatic activation of the vehicle's ventilation system to supply cool air. Such multi-sensory warnings can be used to prevent drowsiness and minimize false-alarm annoyance during continuous driving.<sup>(27)</sup>

## 4.3 Limitations and improvements

Despite the high detection accuracy obtained in this study, limitations must be addressed to ensure the applicability of the developed system. Since its performance was validated in a laboratory driving simulator with 20 participants for 500 min, it does not replicate real-world driving environments. In driving vehicles, engine vibrations, cabin noise, road conditions, and body positions might affect phase information in millimeter-wave radar reflections.<sup>(28)</sup> In addition, driver fatigue caused by long-duration highway driving, night trips, or post-meal circadian dips must be considered through continuous tracking. For performance validation, larger, demographically diverse participant groups must be involved to conduct field-based on-road tests for night-time driving, highway cruising, and dynamic road vibrations.<sup>(28)</sup>

Although respiration (3.75% *MAE*) and heart-rate estimation (6.04% *MAE*) showed high accuracy, yawning (8.72% *MAE*) and blinking (8.38% *MAE*) presented larger errors. These facial micro-motion features might weaken radar reflections because of their small displacement amplitude and limited effective scattering area. As a result, subtle mouth-opening and eyelid

movements are susceptible to multipath interference, signal fluctuation, and subject-to-subject variability. Recent study results have shown that heterogeneous sensor data enable the enhancement of fatigue detection performance by leveraging complementary physiological and behavioral information, suggesting a promising direction for next-generation driver monitoring systems.<sup>(29,30)</sup>

To address related problems, multi-modal sensor fusion methods need to be combined with FMCW. For example, infrared cameras can be used to obtain eye-state and mouth-opening information under low-light conditions and protect privacy. Acoustic sensors can be used to capture yawning-related breathing sounds and respiratory patterns that are difficult to distinguish using radar alone. Through the integration of radar-derived physiological signals with infrared or acoustic measurements, the reliability of facial fatigue indicators can be improved to maintain the advantages of noncontact monitoring and environmental robustness.

Operational robustness against driver occlusions and multi-occupant cabin interference is also a critical factor when evaluating the applicability of noncontact sensing. Conventional optical driver monitoring systems suffer performance degradation when drivers wear sunglasses, face masks, or have dense facial hair.<sup>(31)</sup> In contrast, 77 GHz FMCW radar signals operate in the electromagnetic spectrum where nonmetallic dielectric materials, such as cloth masks, tinted eyeglasses, and facial hair, cause minimal signal attenuation. Because the developed system can measure phase shifts induced by tissue displacement and structural motion, breathing movements, heart rate fluctuations, and jaw displacements during yawning can be detected despite optical facial occlusions.<sup>(31)</sup> Regarding multi-occupant cabin environments, passenger motion shows potential cross-talk interference.

In this study, spatial segmentation using azimuth angular boundaries ( $-20$  to  $0^\circ$  for head,  $0$  to  $20^\circ$  for chest) isolated target reflections at a distance of  $0.6$ – $0.8$  m, filtering out out-of-bound environmental reflections. However, in vehicles with multiple passengers, multi-path reflections or simultaneous passenger movements occur, causing interference in the driver's chest-wall Doppler spectrum. This problem can be solved using high-resolution angle-of-arrival estimation algorithms and multi-target tracking filters to isolate the driver's biological signals.<sup>(31)</sup>

#### 4.4 Ethical deployment and privacy governance

In the adoption of driver monitoring technology, privacy must be protected, following ethical deployment principles and automotive regulations.<sup>(32)</sup> An advantage of FMCW radar over vision-based driver monitoring systems is its privacy-by-design architecture. Data from cameras containing facial features, high-resolution imagery, and eye gazes pose privacy concerns. In contrast, FMCW radar converts reflected electromagnetic waves into anonymous, low-dimensional phase and point-cloud metrics. The developed system processes radar signals on embedded microcontrollers (edge processing), discarding raw point-cloud data after feature extraction and retaining only momentary classification states. This local processing architecture eliminates cloud-based data storage risks and complies with privacy regulations, such as the European Union General Data Protection Regulation. However, the deployment of the developed system requires driver consent through the vehicle's human-machine interface for transparent

data usage and compliance with automotive cybersecurity standards, such as the International Organization for Standardization/Society of Automotive Engineers International standard number 21434 and the United Nations Economic Commission for Europe/Working Party 29.<sup>(32)</sup>

## 5. Conclusion

Traditionally, the detection and prevention of driver fatigue have relied on the driver's self-awareness and consciousness. This method is inherently limited, as drivers struggle to accurately assess their level of fatigue, particularly in its early stages when symptoms are subtle. Extended driving sessions further exacerbate lapses in concentration and attention, intensifying the risks associated with fatigue-related accidents. To address these challenges, we developed a system by employing FMCW radar to detect variations in characteristic values and objectively assess driver fatigue.

In tests with 20 participants over 500 min of evaluation, the system showed a significant classification accuracy of 90.40% (95% *CI*: [87.80%, 92.80%]), with a precision of 85.33% (95% *CI*: [80.10%, 90.20%]) and a recall of 88.20% (95% *CI*: [83.40%, 92.60%]). Statistical hypothesis test results at  $p < 0.05$  indicate that the multi-feature SVM model outperformed alternative machine learning and deep learning baselines. These results support the radar's ability to capture both macro-motions, such as nodding and yawning, and micro-motions, including respiration and heartbeat, with high temporal precision. The phase-based approach effectively distinguishes fatigue-related physiological signals from noise, and frequency-domain analysis validates that heart-rate frequencies consistently fell in the normal physiological range of 1.0–1.7 Hz. Spatial segmentation through azimuth-based region separation further enhanced signal isolation, reducing cross-interference between facial and thoracic reflections and improving clarity in respiration and heartbeat detection.

Compared with existing sensing methods, the developed system has certain advantages. It outperforms optical approaches in nodding and blinking detection without susceptibility to lighting variations or privacy concerns, showing higher accuracy in respiration and heartbeat monitoring than Wi-Fi, RFID, and earlier radar benchmarks. Its overall fatigue detection accuracy improved by 5.4% compared with those of prior FMCW radar systems, underscoring the benefits of multi-modal feature fusion that integrates behavioral and physiological indicators.

The results of this study show that FMCW radar offers a powerful, noncontact, and privacy-preserving solution for driver fatigue detection. By combining macro-motion and micro-motion analyses with spatial segmentation and multi-feature classification, the system shows high accuracy and reliability, contributing to sensor technology development. The results highlight radar's potential to evolve beyond traditional object detection into human-state monitoring for next-generation intelligent sensing platform development for the integration of safety, health, and human–machine interaction.

Performance comparison using fivefold cross-validation showed that the SVM classifier (90.4% accuracy) outperformed ensemble methods (RF, 88.6%) and deep learning architectures (1D-CNN, 84.2%; LSTM, 83.0%). The result indicates SVM's advantages in modeling nonlinear interactions using structured multi-feature vectors under moderate sample sizes. However, deep

learning models have potential for end-to-end radar signal processing if trained on substantially larger datasets. By expanding radar-specific public datasets and using a deep learning-SVM architecture, next-generation intelligent driver monitoring systems can be developed.

Since the developed system's performance was evaluated using 20 participants in a simulated driving environment, it must be tested in real-world driving conditions, under which vehicle vibration, acoustic interference, road-surface irregularities, and variations in driver posture affect radar signal quality and detection performance. To validate system robustness and applicability, larger and more diverse participant groups must be involved, and on-road experiments must be conducted under conditions associated with fatigue, including post-meal drowsiness, nighttime driving, and long-duration highway travel. When using large-scale radar datasets, deep-learning-based models can be applied to enhance feature learning and generalization capability. The introduction of cameras, light detection and ranging, ultrasonic sensors, infrared imaging, or acoustic sensors enables the environmental perception and adaptive calibration of the system. In particular, multi-modal sensor data must be used to enhance the detection ability of subtle facial fatigue indicators, such as yawning and blinking, which is challenging for radar-only systems owing to their small motion amplitudes and weak reflections.

Although the system shows inherent physical resilience against optical occlusions, such as face masks, sunglasses, and facial hair, owing to the penetration capabilities of 77 GHz millimeter waves, the system must be tested in multi-occupant cabin conditions. High-resolution beamforming with expanded multi-driver datasets needs to be introduced to ensure the system's operational reliability in diverse environments. In addition, by combining radar-derived physiological measurements with visual or acoustic information, driver-monitoring systems can achieve enhanced detection reliability, maintaining noncontact operation, privacy protection, and environmental robustness.

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