RF Sensing for Smoking Detection at Oil Fields

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***Abstract*—In this paper, an Ultra-wideband (UWB) Radar sensor is used to detect human gestures while smoking or vaping in potentially dangerous areas such as an oil field or a gas station. Existing smoking detection systems are primarily camera-based, which has a number of drawbacks, including poor illumination, training issues with longer video sequence data, and major privacy concerns. The data collected from a UWB Radar is represented in the form of spectrograms. Three classes are considered, namely cigarette, vape and when the subject is not smoking. InceptionV3, VGG19, and VGG16 deep learning algorithms are used to extract spatiotemporal information from the Spectrogram. Finally, by classifying the Spectrograms into the considered gestures, the smoking and/or vaping is accurately identified. The simulation results show that InceptionV3 can achieve a maximum classification accuracy of 90.00%.**

***Index Terms*—Smoking detection, UWB Radar, deep learning, RF sensing**

I. Introduction

Smoking is a huge problem in oil and gas fields that potentially causes significant monetary and life damages to industries. Various sensors and camera-based smoking detection systems are proposed in the literature to detect smoking activities in high-risk areas. Although the sensor based systems are more common, but they have a limitation of detection human smoking behaviours. Further, they cannot differentiate between smoking and vaping. For this reason, various camera-based approaches are suggested in the literature. For instance, Zhang *et al.* introduce SmokingNet, a convolutional neural network (CNN)-based smoking system that automatically detects smoking gestures from the videos recorded by a camera [1]. The author used Convolution Neural Network based on Transfer Learning model for flower classification [2].A colour based ratio histogram analysis is used in this approach to derive visual clues from appearance interactions between a lit cigarette and its human holder [3]. Similarly, a research utilised image techniques to introduce a system for detection human smoking behaviour. A wearable sensor device was used to detect smoking or non-smoking. The authors provided a way for combining information from the lighter and the wrist-mounted Inertial Measurement Unit (IMU) [4]. In a similar work, researchers developed a novel system that uses photos to detect human smoking or a small amount of smoke, integrating motion detection and background removal capabilities. It was feasible to determine the occurrence of smoking by selecting a smoke area [5]. Using near-infrared (NIR) security camera images, the authors in [6] presented an automated method for detection driver smoking behaviour. However, the camera-based techniques necessitate the recording of the target, which poses severe privacy concerns. Furthermore, bad lighting has an impact on the quality of the images captured, leading to the false classification of smoking gesture. To overcome the limitations of camera-based approaches, this paper presents a Radar-based smoking detection systems, which is immune to external lighting while protecting the user's privacy. Another advantage of our system is its ability to differentiate between smoking and vaping.

Fig. 1: Experimental setup of the proposed Smoking recognition system.

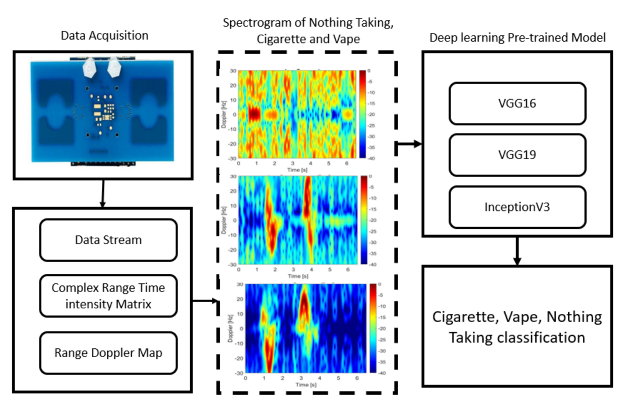
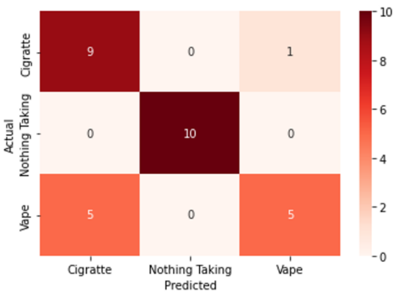


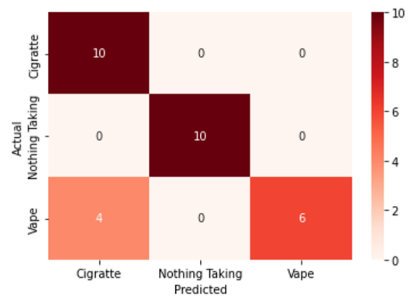
Fig. 2: Flow diagram of the proposed Smoking recognition system.

II. Proposed Scheme

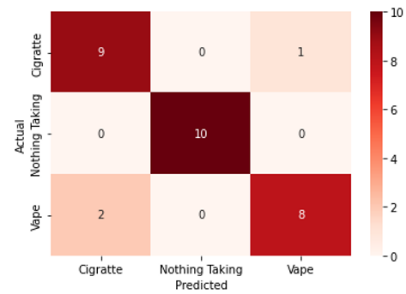
The suggested smoking gesture identification system is based on a UWB Radar sensor (Xethru X4M03). The Radar is based on Novelda's X4 system-on-chip (SoC), which has integrated antennas and a transmitter for extremely accurate



(a) $VGG16$



(b) $VGG19$



(c) $InceptionV3$

Fig. 3: The Confusion matrix of Proposed Model.

distance and movement measurement at frequencies of 7.29 or 8.748 GHz (Detect Micro Movement, Ultra Responsive, Low Power consumption and etc.). Table I shows the system's key setup parameters. For data collection, the target was standing 1 meter away from the Radar. Each of the actions in Fig. 1 took 6 seconds to complete. Through Radar raw baseband data was read using the data float message. DataStream was transformed into a complex range-time-intensity matrix, which was then sent through an MTI filter before being used to create the Doppler range map displayed in Fig. 2. The data was stored as spectrograms, with the x-axis representing time and the y-axis representing Doppler [Hz]. Spectrograms contain information on the dynamic movement of the hands and mouth during the detection of smoking. To capture a sufficient amount of data samples, the target was requested to repeat each gesture many times A total of 150 spectrograms were developed for three considered classes, with 120 being used for training and 30 being used for testing. Three CCN pre-trained model was used for classification, namely VGG16, VGG19 and InceptionV3.

Parameter	Value
Platform	Xethru Radar X4MO3
Instrumental Range	9.6 meters
Target's distance from Radar	1.5 meters
Operating Frequency	7.29 or 8.748 GHz
Transmitter Power	6.3 dBm
Activity duration	6 seconds
Collected samples in each class	50

TABLE I: System's parameters of proposed technique

III. Result and Discussion

Experiments were conducted using a test and train split technique, with 80% of the data being used for training and 20% for testing.The pre-trained models VGG16, VGG19, and InceptionV3 use Adamax as the optimizer and have 15 epochs with a learning rate of 0.001.

The experimental results are shown in Figs. 3b, 3a, and 3c. The fig.3b reveals that most of the classes in VGG19 are accurately identified, with the lowest classification accuracy of 60% for the vape class, which has some similarities to Cigarette. In the same way, the confusion matrix of VGG16 is shown in Fig. 3a, where the classification accuracy for vape is half due to its 50% similarity to Cigarrate. Similarly, except for Vape, Fig. 3c show that the majority of the classes are accurately categorised. The total Accuracy, Precision, Recall, and F1 score of the studied deep learning models are listed in Table II. The Table shows that InceptionV3 outperforms other models, with an overall test accuracy of 90.00%. In terms of precision, recall, and F1-score, the same model produces the best results.

DL Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
InceptionV3	90.00	0.90	0.90	0.90
VGG16	80.00	0.83	0.80	0.79
VGG19	86.67	0.90	0.87	0.86

TABLE II: A comparison of accuracy, macro-recall, macro precision and macro-F1-score between InceptionV3, VGG16 and VGG19.

IV. Conclusion and Future Work

This paper uses a Xethru X4M03 UWB RADAR sensor and deep learning models to detect smoking in an oil field. The proposed scheme can differentiate between vaping and smoking with acceptable accuracy. InceptionV3 outperformed others, with overall accuracy of 90% on all three classes. The long-term goal is to conduct experiments with multiple subjects in various locations.

References

[1] D. Zhang, C. Jiao, and S. Wang, "Smoking image detection based on convolutional neural networks," in *2018 IEEE 4th International Conference on Computer and Communications (ICCC)*, 2018, pp. 1509–1515.

[2] Y. Wu, X. Qin, Y. Pan, and C. Yuan, "Convolution neural network based transfer learning for classification of flowers," in *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)*, 2018, pp. 562–566.

[3] P. Wu, J.-W. Hsieh, J.-C. Cheng, S.-C. Cheng, and S.-Y. Tseng, "Human smoking event detection using visual interaction clues," in *2010 20th International Conference on Pattern Recognition*, 2010, pp. 4344–4347.

[4] J. H. Cho, "Detection of smoking in indoor environment using machine learning," *Applied Sciences*, vol. 10, no. 24, 2020. [Online]. Available: https://www.mdpi.com/2076-3417/10/24/8912

[5] A. D. Odetallah and S. S. Agaian, "Human visual system-based smoking event detection," in *Mobile Multimedia/Image Processing, Security, and Applications 2012*, S. S. Agaian, S. A. Jassim, and E. Y. Du, Eds., vol. 8406, International Society for Optics and Photonics. SPIE, 2012, pp. 51 – 62. [Online]. Available: https://doi.org/10.1117/12.918773

[6] Y. Artan, B. Balcı, A. Elihoş, and B. Alkan, "Vision based driver smoking behavior detection using surveillance camera images," in *Image Analysis and Processing – ICIAP 2019*, E. Ricci, S. Rota Bulò, C. Snoek, O. Lanz, S. Messelodi, and N. Sebe, Eds. Cham: Springer International Publishing, 2019, pp. 468–476.