Radar-Based Exercise Energy Expenditure Estimation with Deep Learning

Auni Nadiah Yusni
College of Engineering
Universiti Teknologi Mara
Shah Alam, Malaysia

Khairul Khaizi Mohd Shariff
Microwave Research Institute
Universiti Teknologi Mara
Shah Alam, Malaysia
khairulkhaizi@my-uni.edu

Mohd Adli Md Ali
Kulliyyah of Science
International Islamic University Malaysia
Kuantan, Malaysia
qunox@iium.edu.my

Ihsan Mohd Yassin
Microwave Research Institute
Universiti Teknologi Mara
Shah Alam, Malaysia

Hanifa Sariman
Faculty of Sports Science and Recreation
Universiti Teknologi Mara
Shah Alam, Malaysia
hanifa4191@my-uni.edu

Aida Yasmin Yazli
College of Engineering
Universiti Teknologi Mara
Shah Alam, Malaysia

2024 IEEE Symposium on Wireless Technology & Applications (ISWTA) | 979-8-3503-5135-4/24/$31.00 ©2024 IEEE | DOI: 10.1109/ISWTA62130.2024.10651717

Abstract— **Exercise is crucial for maintaining a healthy weight and reducing the risk of chronic diseases, yet over half of Malaysia's adult population is overweight or obese due to lack of activity. Accurate monitoring of energy expenditure during exercise is therefore important. A deep learning approach using micro-Doppler radar data is presented to estimate human energy expenditure. Traditional measurement techniques are complex and expensive, while existing wearable sensors have limitations. The method captures micro-Doppler radar signatures from 11 participants performing treadmill walking and running exercises using a 24 GHz continuous-wave radar. The radar signals are preprocessed into time-frequency spectrograms and inputted to a convolutional neural network (CNN) model for training to predict energy expenditure values. The CNN's performance yielded a root mean squared error of 12 kcal/min, providing valuable insights into energy expenditure estimation.**

Keywords— human energy expenditure, radar sensor, deep learning, convolutional neural network

I. Introduction

Over half of Malaysia's adult population is considered overweight or obese, a statistic raising major public health concerns [1]. A key factor contributing to these high rates is the lack of regular physical exercise among Malaysians. To address this and increase activity levels, the Malaysian Ministry of Health released the Malaysian Physical Activity Guidelines. These guidelines align with the Global Non-Communicable Diseases (NCD) Target for 2025, which aims to reduce physical inactivity from 35.2% to 30% [2]. However, a large proportion of the population does not adhere to the national physical activity guidelines [2]. Consequently, there is a need for effective tools to objectively monitor energy expenditure from physical activity. Measuring exercise intensity in terms of energy expenditure is crucial for preventing obesity [3] and lowering the risk of developing chronic diseases [4].

The demand for an accurate and reliable method to estimate energy expenditure (EE) in free-living conditions has grown in recent years since it is important to a better understanding of the role of energy expenditure as a factor in human health. The gold standard for assessing human body energy expenditure in a free-living environment is to use the doubly labelled water (DLW) [5] and calorimetry method [6]. However, these methods are expensive and rely on complex measurement techniques. Recent research has shown that the combination of heart rate (HR) and motion sensors such as Inertial Measurement Unit (IMU) could be used to evaluate energy expenditure [7]. However, the measurement of heart rate is more sensitive to many factors including body size, fitness level, person's emotional stress, environmental temperature and humidity [8]. For IMUs, this method might not be as effective with some physical activities that primarily include upper- or lower-body motion, which can be challenging to identify from a single motion sensor.

Recent developments in predicting energy expenditure during daily activities include the use of radar sensors. These sensors operate by emitting electromagnetic waves and analysing the Doppler shift of the reflected signal caused by human body movements. Radar-based systems offer several advantages over existing methods. Firstly, they guarantee user privacy, as they do not capture visual information. Secondly, they function reliably in all lighting conditions, unaffected by ambient light levels. Finally, radar sensors are generally less expensive and require simpler processing compared to vision-based systems.

Research into using radar to measure physical activity is plentiful, with most studies focusing on recognising human activities like walking, running and sitting [9], [10], [11]. However, estimating energy expenditure during exercise remains less explored. Over the past decade, researchers have attempted to estimate energy expenditure using the mass of radar micro-Doppler estimated from spectrogram [12]. Building on this idea, [13] created regression models for walking and running, achieving an estimation error of under 14% for both activities. However, the complexity of radar spectrograms presents a challenge for these regression models. Human motions during many physical activities can result in intricate micro-Doppler signatures, making it difficult to accurately predict energy expenditure based on simple linear regression model.

Therefore, the objective of this study is to predict energy expenditure using a non-linear model based on deep learning techniques. Specifically, we employ a convolutional neural network (CNN) to estimate energy expenditure from radar spectrogram data. Previous research has demonstrated that

CNN models can learn complex patterns directly from micro-Doppler data, thus eliminating the need for manual feature engineering, such as calculating the mass of the spectrogram.

The rest of this article is organized as follows. In Section II, we describe the details of the proposed methodology which includes details on the system overview, data collection, data pre-processing, Convolutional Neural Network model, and image dataset and CNN training. In Section IV, we present our findings and discuss the paper. Section V, concludes the work.

II. METHODOLOGY

A. System Overview

Fig. 1 illustrates the proposed system. The core of the system utilises a Convolutional Neural Network (CNN) model to predict energy expenditure during exercise on a treadmill. The model is trained on micro-Doppler signals captured by a 24 GHz Continuous-Wave (CW) radar (RF Beam K-LC2 radar [14]) while participants (university students) walked or ran. During exercise, heart rate was also recorded as a ground truth of expanded energy. The captured radar signal is first segmented into short segments, then transformed into spectrograms using Short-Time Fourier Transform (STFT). which serve as the input features for the CNN model.

B. Data Collection

In this study, micro-Doppler data were collected from treadmill exercise using a radar positioned 3 metres behind participants. Eleven volunteers from Universiti Teknologi MARA (UiTM) participated. All participants were in good health and reported no known medical conditions. The study adhered to ethical guidelines and received approval from the Universiti Teknologi MARA ethics committee [15].

Data collection began with a five-minute warm-up walk at 5 km/h. In the main data collection phase, participants started at 5 km/h and the treadmill speed was increased by 0.5 km/h every two minutes, reaching a maximum of 10 km/h. This phase captured ten minutes of walking data (5-7 km/h) and twelve minutes of running data (7.5-10 km/h). In total, 22 minutes of data per participant were collected. Each participant contributed 22 data points (one per minute): 10 for walking and 12 for running. The final dataset comprised 29,040 one-second in-phase and quadrature-phase signals, representing a total recording time of eight hours.

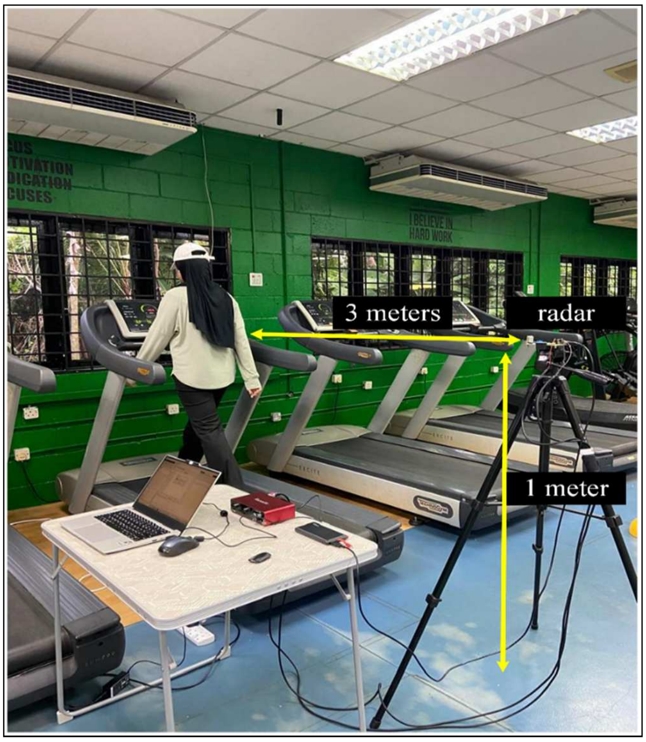

Fig. 2 The experimental setup of a radar-based exercise energy expenditure

C. Data Pre-processing

Data preprocessing is divided into two main parts: noise reduction using a low-pass filter with a cut-off frequency and processing using the short-time Fourier transform (STFT) technique. To obtain a spectrogram, a sliding window is used to divide the digital radar signal into fixed-length samples. The sliding window length is defined by

$$T = (n-1)\Delta T \tag{1}$$

where T is the length of the segment in seconds and ΔT is the sampling interval. We used Hamming window to reduce spectral leakage. Next, we employed short-time Fourier transform (STFT) to convert the one-dimensional radar signal into a time-frequency (TF) representation. For a given discrete radar signal $x[n]$ the discrete Fourier transform (DFT) employing a time-shifted sliding window function of fixed $w[m]$ size is defined by

$$X[k,t] = \sum_{n-1}^{L-1} x[n+m]w[m]e^{-i\frac{2\pi mk}{N}} \tag{2}$$

$$m, k = 1,2,3,\ldots,N-1$$

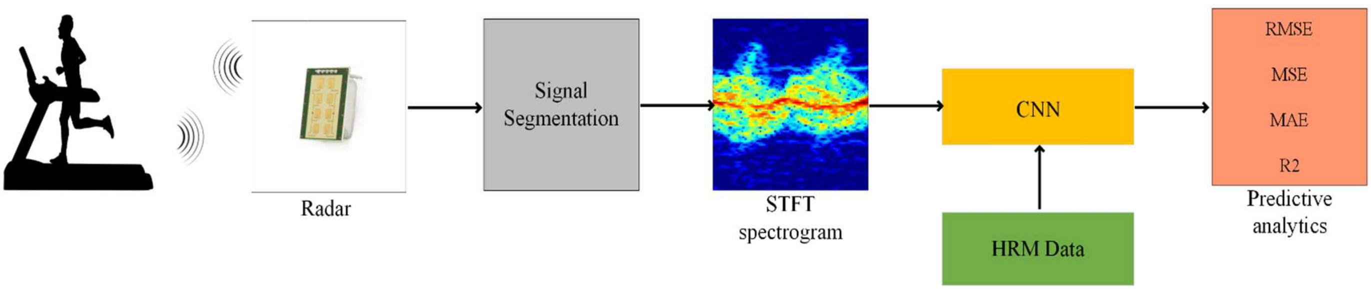

Fig. 1 System proposed

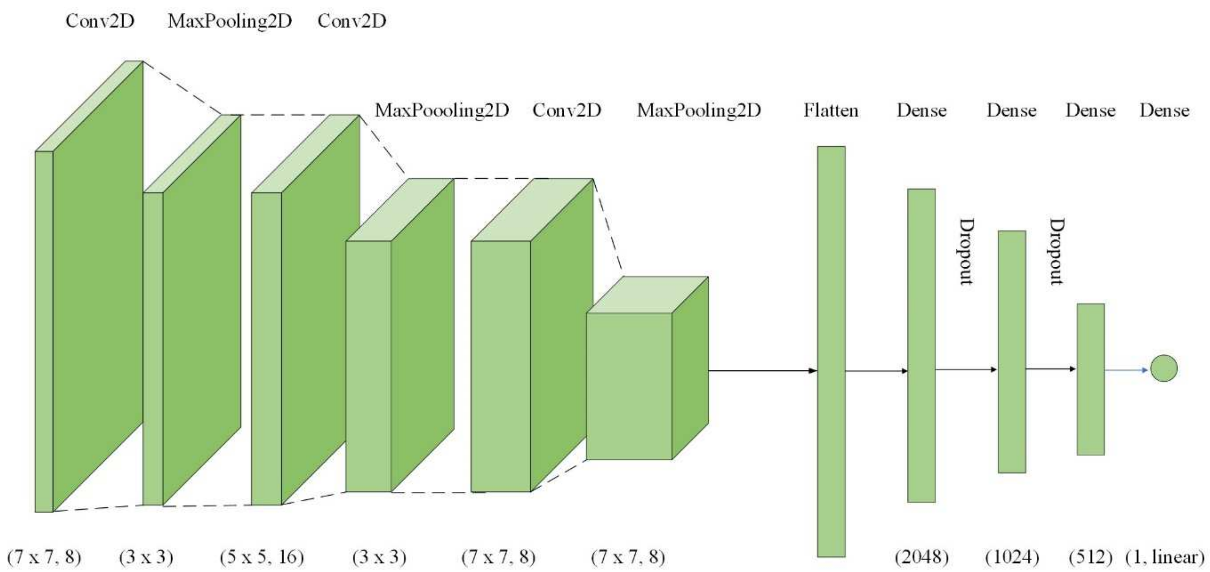

Fig. 3 Proposed CNN architecture

where, $X\ [m, k]$ represents the time-frequency matrix, where k is the frequency bin, t is the frame period, m is the amount of shift and L is the window length. Squaring the magnitude of the STFT, yields the spectrogram. A DFT size of 256 is used. To capture the signal changes that occur between two windows, a 50% overlapping is employed in the sliding window. Any spectral magnitude below -40 dB is removed to noise. Each spectrogram image is visualised with RGB colour and are fixed to a small 128x128 size.

D. Convolutional Neural Network (CNN)

This study utilised a convolutional neural network (CNN) architecture. The first layer used a kernel size of 7x7 to capture large-scale features within the spectrogram. The second convolutional uses a smaller 5x5 kernel. Finally, the third convolutional layer is implemented with even smaller 3x3 kernels. We increased the number of filters used with 8, 16, and 32 for layer 1, 2 and 3 respectively. Following each convolution, a max pooling layer of size 3x3 and a ReLU activation function were implemented. The data was then flattened before feeding into dense layers containing 512, 1024, and 2048 nodes each. Dropout layers were incorporated throughout the network to prevent overfitting and improve generalizability. The entire CNN architecture requires approximately 12.3 MB of RAM. Fig. 3 show the overall architecture of our proposed CNN.

E. CNN Training

The collected dataset is split randomly into 80% for training and 20% for validation in order to train the models using 5-fold cross-validation. We choose Adam as the optimisation algorithm with a learning rate of 10^{-3} and batch size of 32. Additionally, we implemented early stopping with patience set to 10, meaning that after 10 epochs, if the losses do not diminish, the training will stop. Two open-source libraries, TensorFlow and Keras, were used to implement the pre-trained networks. Training was conducted using Google Colab Pro (https://colab.research.google.com) on a Tesla V100 graphics processing unit (GPU).

The root mean square error (RMSE) was used to analyze the performance of the EE models. This metric is commonly used in the field of EE estimation. For additional evaluations, the coefficient of determination (R2) was employed.

III. EXPERIMENTAL EVALUATION AND DISCUSSION

Table 1 presents participants statistical characteristics for EE estimation, included the metrics of the root mean squared error (RMSE) and the coefficient of determination (R^2) of the architecture of CNN. The results obtained using the train and test sets display estimation's performance R^2 scores that approach 0.75 and RMSE equal to 12 kcal/min. Fig. 4 provides the scatter plot of predicted energy expenditure versus measured energy expenditure. Considering R^2, the correlation coefficient between the predicted and measured of EE is relatively high.

From the table 1, reveals that the CNN was able to catch relevant information in the inputs to increase its generalization of different subjects, supported with the low standard-deviation observed. By analysing Fig. 4, our model was revealed to be accurate since an above 0.75 was achieved, indicating that both predicted and measured share the same monotony.

TABLE I. PARTICIPANTS STATISTICAL CHARACTERISTICS AND METRICES

Parameter						Metrics	
	No. of participants	**Age (years)**	**Height (cm)**	**Weight (kg)**	**EE Estimated (kCal/H)**	**Coefficient of determination (R^2)**	**RMSE**
Data are mean ± SD	11	22.18 ± 1.8	165.2 ± 7.2	67.36 ± 3.6	514.3 ± 6.3	0.7473	12

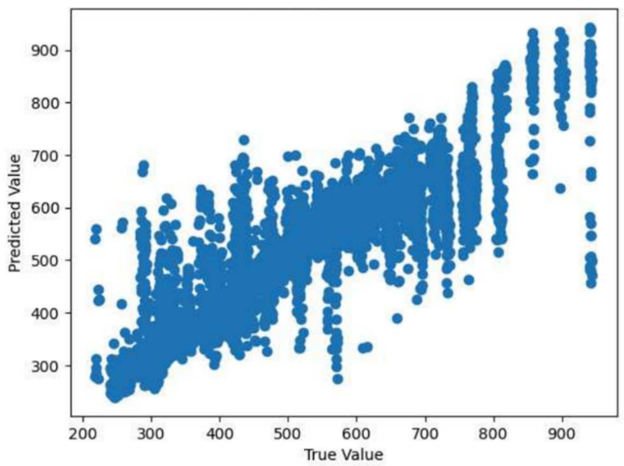

Fig. 4 Scatter plots of predicted energy expenditure vs. measured energy expenditure

IV. CONCLUSION

This work presents and validates a CNN tool for energy expenditure estimation by comparing the predicted EE values to those measured during exercise. A total of 11 individuals participated in the exercises and the results from these studies were promising. It was found that the CNN model provided the accurate estimation of EE, with a root mean squared error of 12 kcal/min. While the research showed encouraging results, the main issue identified is that these techniques were developed and tested using data collected from a limited set of exercises performed. This restricted data may not account for the variability encountered during more diverse activities and in free-living conditions. Addressing this limitation by expanding the data collection to encompass a wider range of real-world activities could improve the generalizability and robustness of the micro-Doppler energy expenditure estimation models.

ACKNOWLEDGMENT

The authors acknowledge Ministry of Higher Education for the Fundamental Research Grant Scheme (FRGS) of project file no: 600-RMC/FRGS 5/3 (004/2022). The authors would like to express their gratitude to the Research Management Institute (RMI) and Universiti Teknologi MARA for their support.

REFERENCES

[1] N. Che Abdul Rahim *et al.*, "Factors Influencing the Levels of Awareness on Malaysian Healthy Plate Concept among Rural Adults in Malaysia," *Int J Environ Res Public Health*, vol. 19, no. 10, p. 6257, May 2022.

[2] Ministry of Health Malaysia 2016, "National Strategic Plan for Non-Communicable Disease (NSP-NCD)," 2016-2025.

[3] M. A. Khanfir *et al.*, "Effects of Different Low-Intensity Exercise Types on Duration, Energy Expenditure and Perceived Exertion in Obese Individuals," *Int J Environ Res Public Health*, vol. 19, no. 8, p. 4893, Apr. 2022.

[4] D. Collado-Mateo *et al.*, "Key factors associated with adherence to physical exercise in patients with chronic diseases and older adults: An umbrella review," *International Journal of Environmental Research and Public Health*, vol. 18, no. 4. MDPI AG, pp. 1–24, Feb. 02, 2021.

[5] T. White *et al.*, "Estimating energy expenditure from wrist and thigh accelerometry in free-living adults: a doubly labelled water study," *Int J Obes*, vol. 43, no. 11, pp. 2333–2342, Nov. 2019.

[6] M. Delsoglio, N. Achamrah, M. M. Berger, and C. Pichard, "Indirect Calorimetry in Clinical Practice," *J Clin Med*, vol. 8, no. 9, p. 1387, Sep. 2019.

[7] C. J. Lee and J. K. Lee, "IMU-Based Energy Expenditure Estimation for Various Walking Conditions Using a Hybrid CNN–LSTM Model," *Sensors*, vol. 24, no. 2, p. 414, Jan. 2024.

[8] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, and B.-H. Koo, "Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature," *Psychiatry Investig*, vol. 15, no. 3, pp. 235–245, Mar. 2018.

[9] M. Muaaz, S. Waqar, and M. Pätzold, "Radar-Based Passive Step Counter and Its Comparison with a Wrist-Worn Physical Activity Tracker," 2022, pp. 259–272.

[10] A. Biró, S. M. Szilágyi, L. Szilágyi, J. Martín-Martín, and A. I. Cuesta-Vargas, "Machine Learning on Prediction of Relative Physical Activity Intensity Using Medical Radar Sensor and 3D Accelerometer," *Sensors*, vol. 23, no. 7, p. 3595, Mar. 2023.

[11] E. Cardillo, C. Li, and A. Caddemi, "Radar-Based Monitoring of the Worker Activities by Exploiting Range-Doppler and Micro-Doppler Signatures," in *2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0&IoT)*, IEEE, Jun. 2021, pp. 412–416.

[12] P. Russo, V. Di Mattia, G. Manfredi, A. De Leo, and G. Cerri, "Radar Doppler technique to estimate the energy expenditure of human physical activities," in *12th European Conference on Antennas and Propagation (EuCAP 2018)*, Institution of Engineering and Technology, 2018, pp. 618 (5 pp.)-618 (5 pp.).

[13] Y. Kim, S. Choudhury, and H.-J. Kong, "Application of Micro-Doppler Signatures for Estimation of Total Energy Expenditure in Humans for Walking/Running Activities," *IEEE Access*, vol. 4, pp. 1560–1569, 2016.

[14] "RFbeam, Standard product K-LC2 Dual Channel Radar Transceiver.," Available: https://www.rfbeam.ch/product?id=5.

[15] "Approval by: The UiTM Research Ethics Committee" (approval no. (REC/08/2023) (ST/MR/218)).