

Thermal Array Sensor Resolution-Aware Activity Recognition using Convolutional Neural Network

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Abstract—Human activity detection and classification (HADC) has become a growing research issue due to the development of sensor technologies, deep learning models, and the need for the safety of people in smart spaces such as buildings and factories. Various researchers have employed sensors with different resolutions for HADC. However, the impact of sensor resolution on the sensor data quality and the accuracy of the deep learning algorithm in this field has been little discussed. In this work, the impact of three different thermal sensor resolutions was investigated while proposing a convolutional neural network (CNN). The results showed that the proposed CNN displayed a resolution-aware performance, being able to contain the impact of a change in thermal sensor resolutions. Although the CNN model had lower accuracy as the resolution was changed from 32x32 to 4x4H and 4x4, respectively. However, it was able to reduce the type errors and maintain an average accuracy of 82.74%.

Index Terms—Activity Recognition, Deep Learning, Thermal Sensor, Sensor Resolution.

I. INTRODUCTION

Detecting human activities using sensor-based methods has attracted widespread attention in homes, factory shop floors and smart building sectors [1]. Currently, Human activity detection and classification (HADC) often comprises sensors (environmental, visual, and wearables), combining capabilities to provide and enable monitoring in different fields [2]. Existing technologies such as camera-based detection schemes expose privacy from a camera, thus invading the privacy of people whose activities are being monitored [3]. Also, conventional wearable approaches cause discomfort to users and sometimes require the cooperation of users for efficient and successful deployment.

Compared to the approaches above, a thermal sensor detects activity by concentrating the infrared (IR) energy radiated by an object onto the photo-detectors [4]. The photo-detector, in turn, transforms that energy into an electrical signal relative to the IR energy emitted by the object with developed technology for improved and accurate activity detection. Thermal sensors generally have distinct image pixel characteristics due to the intentional distinction between their image generation processes [5]. In recent years, some authors have proposed diverse methodologies for detecting and recognizing objects in thermal infrared imagery, particularly in sensing and human activity (dynamic and static) recognition.

The authors in [5] provided insights on a wide range of sensors used for HADC. The following thermal imaging sensors' resolutions were outlined and described: 4x16, 8x8, and 16x16. Emphasis was also placed on positioning and right sensor placement as thermal array sensors have a narrow field of view (FoV). In [6], sensor data from an 8x8 resolution thermal sensor was extracted and processed using the J-Butterworth and the Kalman filter. In [7] to reduce noise in the raw data and achieve an enhanced HADC mechanism, the Long-Short-Term Memory algorithm was the model used in [6] to extract the data feature. However, the authors failed to explain the environmental setup for their testbed.

In [8], two 4x16 low-resolution thermal sensors were used to collect activity data. The sensors were stationed halfway along a wall, and six different algorithms were trained. The feed-forward neural network gave the best activity detection accuracy, justifying the detection capability of Deep Learning (DL) models for the purpose of HADC [9]. However, there is no major evidence of existing work where the impact of thermal array sensor resolutions has been fully investigated to justify the impact or not of the resolution of thermal sensors on the overall performance of HADC systems. Although, [10] carried out similar modeling and achieved an accuracy of 80% and 90% performances for vision-based and classification-based workflows using the feature classification-based model. However, their model was based on predicting occupancy only.

Lower resolution thermal sensors have a narrow FoV and are usually implemented in pairs to widen their FoV [5]. Their advantage is that they introduce low noise due to little interference during data gathering. On the other hand, a higher resolution thermal sensor has a wider FoV and does not need to be paired up with other thermal sensors. However, they are subjected to noise interference [11]. There is a need, therefore, to design a DL model that can handle the introduction of noise interference as the resolution of sensors increases, as DL models are also efficient in recognizing human dynamic activities in line of sight and non-line of sight scenarios.

This study aims at exploring the resolution aware capacity of three (3) different thermal sensor resolutions to train a DL model for activity recognition by collecting data from these three different sensors. The approach adopted in this work is different from recent research, which only focuses on detection

or classification of human activity and not resolution-aware capacity. The main contribution of this work, with respect to the state of the art, is the implementation of a Convolutional Neural Network (CNN) applied to three different resolutions of Omron Thermal Sensors (4x4, 4x4H, and 32x32) for HADC and evaluating the resolution aware ability of each sensor using the DL approach.

The contributions of this work are as outlined below:

- 1) To design a non-intrusive and low-cost activity recognition system test bed setup using three different thermal sensors with different resolutions as the data acquisition device.
- 2) To develop a CNN model that is resolution-aware and able to handle the noise introduced by the increased resolution of the thermal sensors.
- 3) To investigate the impact of sensor resolution and prove that the model is resolution-aware, i.e., sensor data and resolution do not affect the ability of the algorithm to effectively detect and classify human activities.

The paper arrangement is thus: Section II is the proposed framework, architecture, hardware design, and testbed. Section III was devoted to experimental results and Section IV concluded the paper.

II. SYSTEM MODEL

This section provided the background of the developed framework, description of the sensor and hardware testbed, software configuration, and the evaluation criteria on various sensor prediction models. The stages of the HADC model include raw sensor data collection in form of heatmaps, data preprocessing to temperature values and data segmentation, feature extraction and engineering, and the DL model.

A. Sensors Testbed and Setup

The system was designed by placing the sensor on a ceiling located 2.5m meters away from ground level as shown in Fig.1, measuring the heat received from the object and converting it to temperature data. The choice of the ceiling is to achieve a good FoV in line with the product data-sheet hence proper placement of the sensor was established to ensure appropriate FoV of the sensors to capture the object effectively [12]. Two activity detection scenarios were designed namely; activity (class 1) and no activity (class 0). The Omron sensors were used because of their low noise, stable temperature values, and easy-to-use properties.

The OMRON thermal sensor was developed with thermal fire technology and which include a low noise amplifier, a cap with a silicon lens, MEMS thermopile sensor chips, and a microcontroller unit for converting analog signals to digital signals. The thermal sensor technology recognizes the combination of thermopile elements and ASICs into a unified platform, resulting in a super-compact footprint and high resolution. The silicon lens captures radiated heat from an object and directs it to the module's thermopile. An electromotive force is generated within this module and used to calculate the temperature value via an analog circuit made available

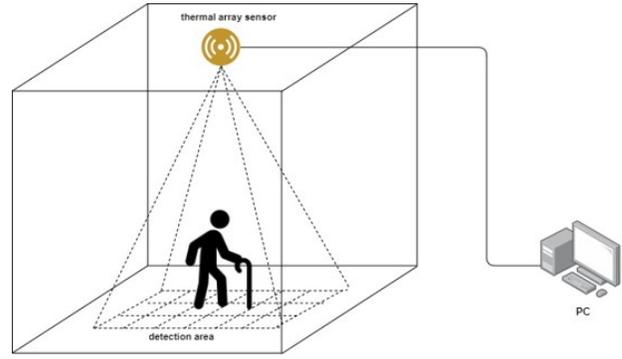


Fig. 1. Sensor Placement in the Smart Space at 2.5m from the ceiling to ensure target object is within FoV

through the use of the I2C protocol [13]. The description and specifications of the sensors used are shown in Table I.

TABLE I
DESCRIPTION OF SENSORS USED

Sensor Name	D6T-44L-06	D6T-44L-06H	D6T-32L-01A
Sensor Elements (in Pixels)	16 (4 x 4)	16 (4 x 4)	1024 (32 x 32)
Sensors Standpoint: X-direction Y-direction	X = 44.2° Y = 45.7°	X = 44.2° Y = 45.7°	X = 90.0° Y = 90.0°
Distance: X & Y	X = 1.6m Y = 1.69m	X = 2.44m Y = 2.53m	X = 6m Y = 6m
Temperature Detection Range	5 – 50°C	5 – 200°C	0 – 200°C
Current Consumed	5 mA	5 mA	19 mA

The sensors capture multiple frames within one second because they are built to update temperature data every 300 ms or less. Evaluation was performed by connecting the sensors to the evaluation boards and Arduino with a harness cable as shown in Fig. 2. Output specifications of the sensors are digital values (binary codes) corresponding to the reference temperature (known as heatmap). Data capture was performed and processed using a low-cost desktop computer with an Intel(R) Core(TM) i5-8500 CPU 3.00GHz processor, 8GB RAM, and an NVIDIA GeForce GTX 1050 GPU running on Windows 10. The OMRON sensor was linked to an Arduino board- a microcontroller- to carry out this process. The Arduino board reads sensor data and transmits it to the sensor evaluation board via the UART interface.

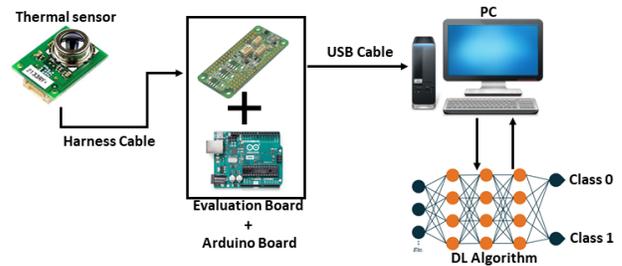


Fig. 2. Set up and Hardware Configuration

B. Hardware Requirements, Assemble and Software Configuration

Hardware requirements and functionality are as follows: Arduino Board (MKR WiFi 1010), Omron Sensor Evaluation Board (2JCIE), Omron Sensors (D6T-44L-06, D6T-44L-06H, D6T-32L-01A), Omron Harness Cable (2JCIE-HARNESS-01 for Arduino), USB and PC. The process of the hardware assembly is shown in Fig. 2 and Fig. 3 are:

- Solder the evaluation board and connect it to the Arduino board.
- Connect the USB cable to the Arduino board.
- Connect the omron harness cable to the omron evaluation board.
- Connect the other end of the harness to the Omron sensor.
- Place the thermal sensor in the human detection area.
- Download Arduino IDE and install the package and set up the driver.
- Connect the Arduino board to PC using the USB cable.

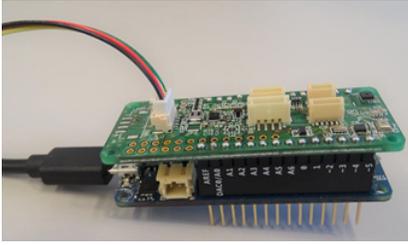


Fig. 3. Connecting the Sensor to the Evaluation Board prior to Placement

The steps for software configuration, visualization and data acquisition are as follows:

- Download Arduino IDE from their official site (www.Arduino.cc).
- Run the installation package and wait until the installation is finished.
- Plug the assembled Arduino device, if there is a package installation notification, click to install them.
- Arduino IDE is ready to use, write the code and upload it using the upload button to run the code to the sensor.
- Add Arduino SAMD Core Library to Arduino IDE > Tools menu > Boards > Boards Manager.
- Navigate to Device Manager in your Windows, make sure that Arduino MKR WiFi 1010 is available in COM & LPT ports.
- Set up the board and ports to be used in Arduino IDE > Tools > Board > Arduino SAMD (32 Bits) Boards > Arduino MKR WiFi 1010, and also the port > Tools > Port > Arduino port.
- Select the thermal sensor type and Upload the thermal data sketch to the Arduino interface as Zip file > Sketch > Include Library > Add .ZIP library
- Compile and upload the code to generate the sensor data from the thermal sensor
- Download the processing application to update temperature values generated from the Arduino interface.

C. Proposed Convolutional Neural Network (CNN)

Due to growing computational resources, CNN has been widely adopted as a result of its full potential. [14], [15]. CNN extracts feature maps from a given dataset and learns patterns from the convolutional operations of such a dataset. The CNN model implemented in this work was built using the popular deep learning platform - Keras library on a Jupyter notebook. Standard Python libraries were used to provide optimized implementations of each sensor data. Although CNN is commonly used for image datasets, by using the 1D-CNN, its benefits were exploited. Furthermore, with little or no feature engineering, 1D CNNs have demonstrated to offer state-of-the-art performance on HADC tasks. As shown in Figure 4, the generated heat map, converted to temperature data is captured by the CNN model for the purpose of the HADC.

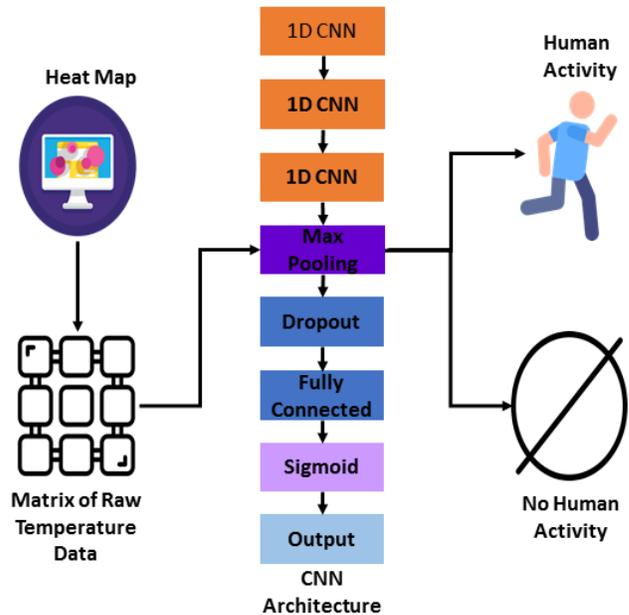


Fig. 4. Overall architecture of the HADC model showing the proposed 1D CNN model and its layers

TABLE II
PARAMETER SETTINGS FOR PROPOSED CNN MODEL

CNN Layer	Filter Number	Kernel Size	Activation Function
1st Layer	64	5	ReLU
2nd Layer	64	7	ReLU
3rd Layer	256	7	ReLU
Max Pooling	2		
Dropout	0.5		
Loss Function	Binary Cross Entropy		
Optimizer	Adam		

The proposed 1D CNN consists of three (3) stacked convolutional layers with optimal parameter selection on each layer. The set up of each layer and criteria is shown in Table II. The convolutional layers summarize the presence

of the input features by creating a feature map and applying learned filters to the input dataset. The max-pooling layer down samples these feature maps by summarizing the features in patches [16]. To suppress over-fitting and co-dependency among neurons during the training process, a drop-out of 0.5 neurons is added before the fully connected layer. The Adam optimizer was used, given its benefits. The generated dataset is split into 80% for training and 20% for testing. Up-sampling was performed to deal with imbalanced data as activity data was far greater than non-activity data. Finally, the dataset is scaled using the standard scaler.

III. PERFORMANCE EVALUATION AND RESULT

This section presents the experimental results for the proposed model on the three different sensor resolution types. As shown in Fig. 5, the proposed 1D CNN showed resilience in attaining appreciable linear accuracy as well as reduced errors despite the impact of sensor resolution. The limiting factor of using a larger thermal sensor array is noise. However, in this work, there is no analysis of the amount of noise received from the higher resolution sensor. Although, the aim of proposing the DL model implemented in this work is to ensure that the performance of the HADC model is not affected as the resolution of sensors increases. The proposed model achieved accuracy of 78.47%, 78.72% and 91.02% for 4x4, 4x4H and 32x32 thermal resolutions, respectively. It is agreeable that a change in resolution affects accuracy. However, the proposed CNN model maintained a reasonable average performance of 82.74%, thus resolution-aware.

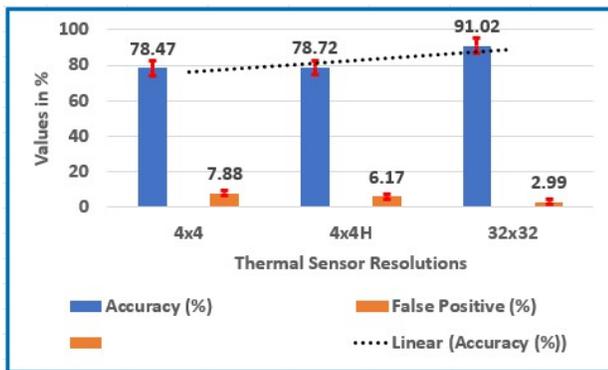


Fig. 5. Accuracy and False Positives of the Thermal Sensor Resolutions for Activity Recognition

Also, the result is presented with confusion matrix showing the true positive, true negative, false positive and false negative of the sensors in Fig. 6, Fig. 7, and Fig. 8 respectively. Since an increase in resolution tends to increase the noise in the sensor data, the goal of the CNN is to take care of the impact and ensure that type I error (false positive) is kept to a minimum no matter the increase in the resolution of the sensor and data. From the confusion matrix, it can be observed that the false positive or type I error of the proposed CNN for 4x4, 4x4H, and 32x32 resolutions are 7.88%, 6.17% and 2.99%

respectively. In the same vein, the type II error was effectively managed too as shown in Fig. 9.

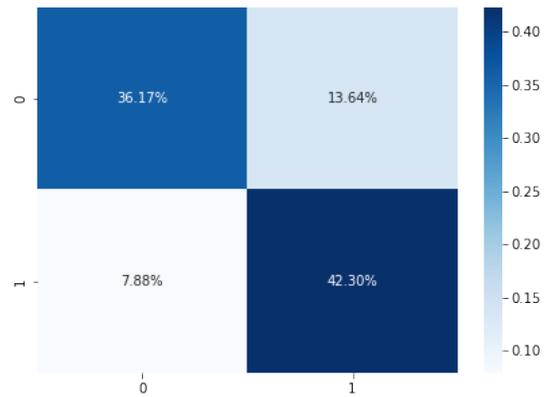


Fig. 6. Confusion Matrix of the proposed CNN using 4x4 Resolution Thermal Sensor Data

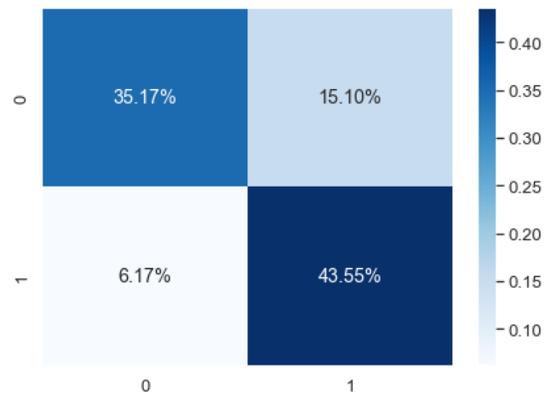


Fig. 7. Confusion Matrix of the proposed CNN using 4x4H Resolution Thermal Sensor Data

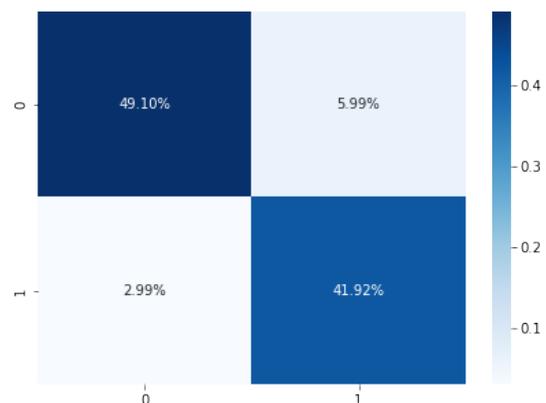


Fig. 8. Confusion Matrix of the proposed CNN using 32x32 Resolution Thermal Sensor Data

IV. CONCLUSION

In this work, a CNN model was developed for detecting and classifying human activities using different thermal sensor

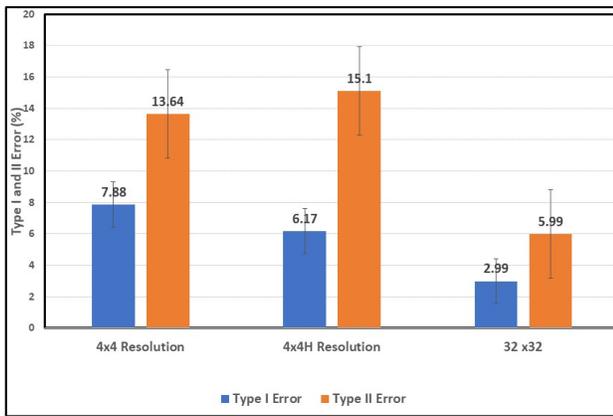


Fig. 9. CNN effectively handled the Type I and II errors despite the increase in thermal sensor resolution

resolutions. The result shows that irrespective of the resolution of sensors used in capturing the data, the proposed CNN showed resilience in its ability to effectively detect and classify the activities. It is a future research direction to explore other DL and ensemble learning candidates as a way of investigating their capabilities in comparison to the proposed CNN. The proposed CNN showed appreciable accuracy performance using thermal sensor resolutions of 4x4, 4x4H, and 32x32 respectively.

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REFERENCES

- [1] C. I. Nwakanma, F. B. Islam, M. P. Maharani, J.-M. Lee, and D.-S. Kim, "Detection and Classification of Human Activity for Emergency Response in Smart Factory Shop Floor," *Applied Sciences*, vol. 11, no. 8, 2021. [Online]. Available: <https://www.mdpi.com/2076-3417/11/8/3662>
- [2] L. Tao, T. Volonakis, B. Tan, Y. Jing, K. Chetty, and M. Smith, "Home Activity Monitoring using Low Resolution Infrared Sensor," *CoRR*, vol. abs/1811.05416, 2018.
- [3] Y. Wu, H. Liu, B. Li, and R. Kosonen, "Prediction of Thermal Sensation using Low-cost Infrared Array Sensors Monitoring System," *IOP Conference Series: Materials Science and Engineering*, vol. 609, p. 032002, October 2019.
- [4] F. Riquelme, C. Espinoza, T. Rodenas, J.-G. Minonzio, and C. Taramasco, "eHomeSeniors Dataset: An Infrared Thermal Sensor Dataset for Automatic Fall Detection Research," *Sensors*, vol. 19, no. 20, 2019.
- [5] B. Fu, N. Damer, F. Kirchbuchner, and A. Kuijper, "Sensing Technology for Human Activity Recognition: A Comprehensive Survey," *IEEE Access*, vol. 8, pp. 83 791–83 820, 2020.
- [6] C. Yin, J. Chen, X. Miao, H. Jiang, and D. Chen, "Device-Free Human Activity Recognition with Low-Resolution Infrared Array Sensor Using Long Short-Term Memory Neural Network," *Sensors*, vol. 21, no. 10, 2021.
- [7] A. A. Trofimova, A. Masciadri, F. Veronese, and F. Salice, "Indoor Human Detection Based on Thermal Array Sensor Data and Adaptive Background Estimation," *Journal of Computer and Communications*, vol. 5, no. 4, 2017.
- [8] S. Shelke and B. Aksanli, "Static and Dynamic Activity Detection with Ambient Sensors in Smart Spaces," *Sensors*, vol. 19, no. 4, 2019. [Online]. Available: <https://www.mdpi.com/1424-8220/19/4/804>
- [9] V. B. Semwal, A. Gupta, and P. Lalwani, "An Optimized Hybrid Deep Learning Model using Ensemble Learning Approach for Human Walking Activities Recognition," *The Journal of Supercomputing*, 2021.
- [10] B. Sirmacek and M. Riveiro, "Occupancy Prediction Using Low-Cost and Low-Resolution Heat Sensors for Smart Offices," *Sensors*, vol. 20, no. 19, 2020.
- [11] D. Jahier Pagliari and M. Poncino, "On the Impact of Smart Sensor Approximations on the Accuracy of Machine Learning Tasks," *Heliyon*, vol. 6, no. 12, p. e05750, 2020.
- [12] A. Naser, A. Lotfi, and J. Zhong, "Adaptive Thermal Sensor Array Placement for Human Segmentation and Occupancy Estimation," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 1993–2002, 2021.
- [13] "Omron Electronic Components: White Paper on 'D6T MEMS Thermal Sensors: Non-Contact Thermal Sensor for Contact-less Measurement'." 2018. [Online]. Available: <https://www.omron-ecb.co.kr/product-detail?partNumber=D6T>
- [14] T. Huynh-The, C.-H. Hua, Q.-V. Pham, and D.-S. Kim, "MCNet: An Efficient CNN Architecture for Robust Automatic Modulation Classification," *IEEE Communications Letters*, vol. 24, no. 4, pp. 811–815, 2020.
- [15] S.-H. Kim, J.-W. Kim, W.-P. Nwadiugwu, and D.-S. Kim, "Deep Learning-Based Robust Automatic Modulation Classification for Cognitive Radio Networks," *IEEE Access*, vol. 9, pp. 92 386–92 393, 2021.
- [16] D. Xiao, Y. Chen, and D. D.-U. Li, "One-Dimensional Deep Learning Architecture for Fast Fluorescence Lifetime Imaging," *IEEE Journal of Selected Topics in Quantum Electronics*, vol. 27, no. 4, pp. 1–10, 2021.