Smart Clothing and On-Device Gesture Recognition for Controlling Smart Buildings Systems

Adrian-Vasile Catană
MintViz Lab, MANSiD Research Center
Ştefan cel Mare University of Suceava
Suceava, Romania
adrian.catana@usm.ro

***Abstract*— More and more devices are integrated into buildings, transforming them into intelligent structures that adapt to their occupants. Due to the large number of integrated systems and the continuously growing complexity, it is difficult for users to control these systems. This work explores the possibility of using smart clothes to control a building using hand gestures. A prototype device was developed that can be easily integrated into ordinary garments by making minor modifications. The design of the device prioritizes relatively small dimensions, to facilitate easy integration, low energy consumption, modularity, efficiency, and ease of use. Gesture acquisition was achieved using a 6-axis IMU (Inertial Measurement Unit). Classification of gestures was implemented directly on the wearable device using artificial intelligence (AI) techniques. Gesture recognition was achieved solely through real-time processing available on the device, adapted to limited computational power available, enabling controlling smart building systems without the need for a cloud service or internet. Wearing a smart device-integrated garment, the user can control various systems in a smart building, in an easy and more natural manner, using hand gestures.**

Keywords—smart clothing, smart building, gesture recognition, machine learning, wearable technologies

I. Introduction

An increasing number of individuals [1] are adopting smart devices that automate the buildings in which they live or conduct their professional activities. These devices not only enhance the perceived comfort of their occupants but also assist them in optimizing their work, operating in a better-suited environment, or efficiently monitoring certain parameters to safeguard their health, such as air quality.

In a smart building, controlling a wide range of devices [2] can be challenging for users due to their complexity [3]. For regular building occupants, controlling it often occurs in a non-standardized manner [4], using fixed dedicated control panels for some systems, buttons, remote controls, etc., for others. This creates difficulties due to the confusion it causes, the user is unsure which interfaces to use to control a particular system. At other times, it puts the user in the impossibility of efficiently controlling multiple systems simultaneously due to the physical distance between different control interfaces. For example, the temperature and air conditioning intensity are controlled from a control panel on a wall, while the light switch has certain dedicated buttons located elsewhere. General control panels are installed in some buildings, but these are usually available to the administrator who has full access to all systems.

Other approaches involve controlling them through dedicated applications on mobile phones [5], smartwatches and smart bracelets [6], [7], or the utilization of new devices for controlling [8] or obtaining feedback [9], [10] from

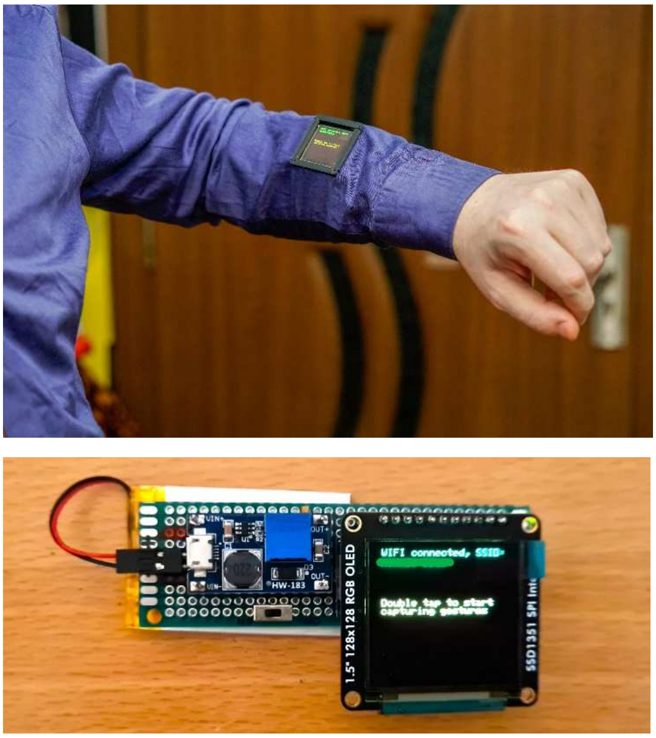

Fig.1. A user wearing a smart garment (top), detail with integrated electronic device (bottom)

building systems. While these systems offer added convenience to users, they often entail diverting their attention from ongoing activities. Simple adjustments, like modifying the temperature, require several sequential steps, including unlocking the device, locating the relevant application, navigating through its interface, and finally making the desired adjustments.

Some buildings employ systems that align with the concept of calm technology [11]. This entails designing technology to be at the periphery of the user's attention and sometimes to fade into the background. Technology designed using this concept aims to provide the user with a seamless experience without requiring them to keep it at the forefront of their attention. It operates in the background without distracting the user with constant notifications with respect to the user's focus. This concept entails the building autonomously adjusting its parameters through sensors integrated into specific locations from which to gather data for self-regulation. This eliminates the need for occupants to directly interact with its systems, as the building automatically adapts to the users' needs.

A smart building where all integrated systems are based on the concept of calm technology is ideal. However, in practice, this is more challenging to achieve, especially in

979-8-3503-4929-0/24/$31.00 ©2024 IEEE

multi-user environments. Users have different preferences and may prefer certain parameters to be adjusted differently than what seems theoretically ideal. For example, lighting, despite accumulated knowledge in the specialized literature [12] regarding color temperature [13], intensity [14], and light distribution based on space, activity, and other parameters, some building occupants may prefer a different type of lighting in their workspace. Hence, an efficient interaction method between users and the smart building systems is necessary to ensure that users do not feel constrained by the building to accept certain automatic adjustments contrary to their will, but rather perceive these adjustments as beneficial to them, who are in control.

II. SYSTEM DESIGN

A. Design Approach

The objective was to develop a smart garment enabling user control of the systems within a smart building through hand gesture recognition. To accomplish this, a prototype device was created that could be easily integrated into clothing with minimal adjustments. The target was a small and lightweight device with low energy consumption, which can work independently of a cloud service or internet, as long as the communication with the other building systems requires only the local network. This would enable the occupants of smart buildings to control their systems, more naturally and easily, through hand gestures.

B. Apparatus

The wearable device consists of an Arduino Nano RP2040 Connect development board [15], a voltage stabilization and boost circuit to 5V, a 1.5" color OLED display [16], and a 3.7V 400mAh single cell LiPo battery that powers the device. The wearable device was integrated into the upper part of the sleeve of a garment.

The device is adaptable according to the user's needs, being able to operate with or without the attached screen. In the screenless mode, its weight decreases to 32 grams, while still providing the same functionality except for visual indications, and 44 grams with the display. The majority of the weight comes from the prototyping board and the boost module used at this prototyping stage. Miniaturization is possible in a stage closer to a final version.

The Arduino Nano RP2040 Connect offers multiple functionalities while maintaining a small form factor, identical to the Arduino Nano. Processing on this board is accomplished by the Raspberry Pi RP2040 [17] microcontroller equipped with a dual-core 32-bit Arm Cortex-M0+ processor, ensuring fast processing and energy efficiency. The use of this development board is attributed to its excellent specifications and its suitability for wearable devices. It features extensive connectivity options thanks to the U-blox Nina W102 module [18]. This module can be programmed to function as a Bluetooth 4.2 radio or as a Wi-Fi compatible with the IEEE 802.11b/g/n single-band standard. Communications between this module and other devices are made through a small integrated Planar Inverted-F Antenna (PIFA), maintaining overall compact dimensions. Alongside other modules present on board is the LSM6DSOXTR, an inertial measurement unit (IMU) module that includes a 3D gyroscope, 3D accelerometer, and a Machine Learning Core on chip. The data from this module will be used for gesture detection purposes.

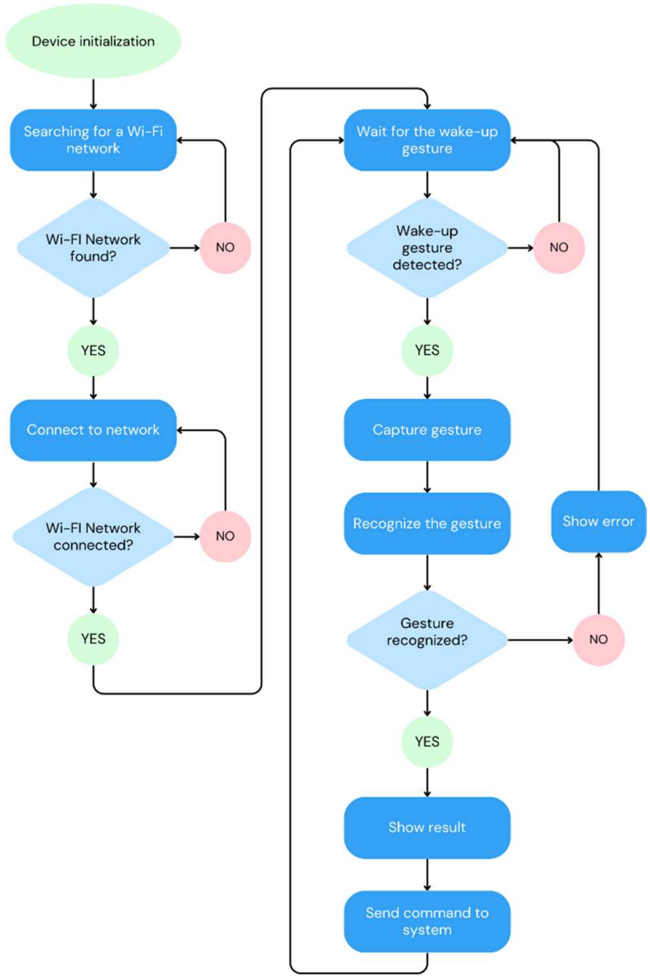

Fig.2. Flow diagram of the smart garment gesture-based system.

C. Smart Clothing

Using smart clothing offers several advantages. One of these is increased comfort, as their use is more convenient compared to separate devices such as mobile phones or smartwatches. Another advantage is the ease of use, control is facilitated through gestures, eliminating the need for direct interaction with the devices through screen touch and button pressing. It reduces the risk of the device being forgotten, as it is permanently attached to the garment. In specific work environments where uniforms are utilized, the possibility of not having the device on hand is entirely eliminated through the adoption of smart uniforms integrating electronic components.

D. Technical Operation and Functionalities

From the user's perspective, the operation is straightforward. By using the smart garment, the user can control the systems of a smart building through hand gestures. Upon activation, an initialization text appears on the screen, after which the device connects to the Wi-Fi network. Successful connection is indicated on the screen along with usage instructions. To control a building system, the smart garment must be activated to capture the gesture and send the corresponding command. The smart garment is activated by the user through a wake-up gesture, performed by double-tapping the active area of the garment where the electronic device is integrated. Once the user performs the wake-up

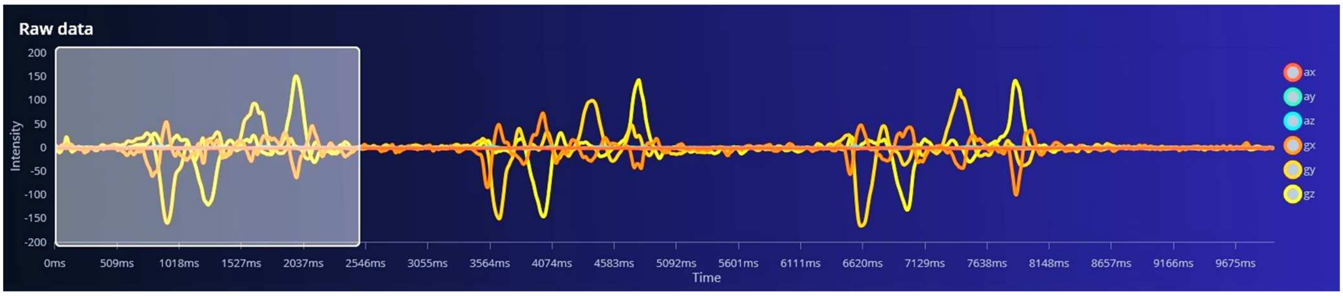

Fig.3. The graphical representation depicts raw data from the IMU, illustrating linear accelerations and angular velocities.

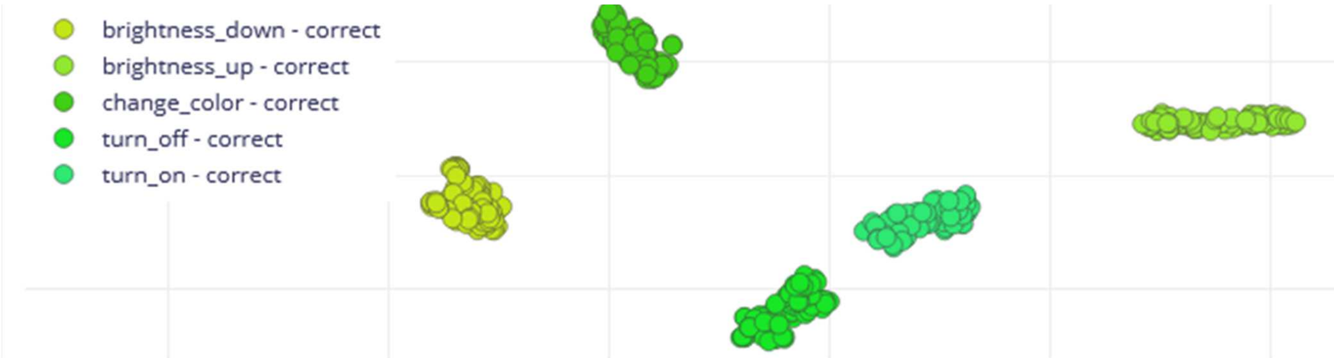

Fig.4. Representation of the data set.

gesture, it is analyzed onboard the device. The detected gesture is displayed on the screen, and the command is sent to the corresponding system. If the user wishes to execute a new command, they must repeat the wake-up gesture and perform the appropriate gesture for the desired command in the air.

The device wake-up command and preparation for gesture detection were performed using the standard interrupt option on double-tap integrated into the LSM6DSOX IMU chip. After waking up, the user's movement is measured by the IMU in high-performance mode at a sampling rate of 104 Hz. The measurement utilizes data from both the 3-axis accelerometer and the 3-axis gyroscope. These data are analyzed after the gesture is performed using the AI model stored in the device. As a demonstrative example, the device was used to control a Philips HUE lighting system [19]. The implemented gestures for control were: *turn on*, *turn off*, *brightness up*, *brightness down*, and *change color*. The *turn on* gesture takes the form of a vertically drawn square, while the *turn off* is accomplished by drawing a circle in the air. *Brightness up* involves a vertical plane movement, *brightness down* entails a horizontal plane movement, and *changing colors* is achieved through a horizontal semicircular movement. Communication between the smart garment and the Philips HUE system is established directly using the API provided by the manufacturer. The use of the device is not limited to a specific system. Controlling the lights is just one proposed scenario.

III. Gesture Recognition

A. ST Machine Learning Core

There are several methods for gesture detection, as outlined in the specialized literature, one of which entails utilizing an IMU module for data acquisition and subsequent classification. The development board employed in this study is equipped with a 6-axis IMU module and a Machine Learning Core, providing ample capabilities for gesture detection and classification.

The IMU module used is the LSM6DSOX [20], one of the first chips that integrate a Machine Learning Core, developed by STMicroelectronics. Its utilization relieves the microcontroller (MCU) from certain stages of IMU data processing and accelerates the gesture recognition process while simultaneously keeping a high energy efficiency. According to the manufacturer, power consumption is only 550 µA in combo high-performance mode [20]. When the Machine Learning Core is used, the additional energy consumption is only 13 µA. Fast and energy-efficient recognition is facilitated by shifting the processing of certain application algorithms from the main processor to the IMU module, which integrates specifically optimized hardware for efficient calculations in tasks such as pattern searching, motion intensity detection, and position recognition.

The Machine Learning Core can be trained to recognize specific movements and patterns. This is achieved by utilizing up to 8 available decision trees that can be used independently or simultaneously. A decision tree is a hierarchical decision model, similar to a tree, composed of multiple configurable nodes, each characterized by a binary decision condition of the "if-then-else" type. The data from the sensor pass through several of these nodes and are evaluated based on various parameters, ultimately reaching the leaf nodes where the classification result resides. The use of this type of classifier reduces the complexity of data processing and analysis, provides a swift response, and can be employed even on devices with limited computational resources.

Although the integrated Machine Learning Core module in the chip performs well with good accuracy when dealing with repetitive motions, such as identifying a process based on vibration patterns, such as water boiling when the device is attached to a kettle, or identifying activities like walking, running, or jumping, etc., when it comes to movements such as hand gestures forming geometric shapes or patterns drawn in the air, recognition accuracy decreases.

The capability of the integrated Machine Learning integrated into the chip was tested on hand movements in the air. Data from the 3-axis accelerometer were recorded and saved on the device, then transferred to a computer for labeling and subsequent decision tree construction. The decision tree building was built using the official software from ST, called Unico GUI [21]. Additionally, the popular software Weka [22], widely used in machine learning and data mining, was also attempted for constructing the binary tree. Five gestures were chosen for classification by the device. During the training phase, the number of samples provided ranged from 5 to 40 for each class, depending on the training session, and each time was evenly distributed among the classes. Unfortunately, the recognition accuracy was below 40%. After several tests, incorporating data from the gyroscope along with the accelerometer data, recognition accuracy remained low, with slight improvements compared to using the accelerometer exclusively.

B. *TinyML*

TinyML [23] refers to the use of machine learning technologies on low-power devices targeting particular battery-powered devices. The use of TinyML offers several advantages compared to cloud processing. One of these is low latency, as the device processes data locally using the AI model stored onboard, providing faster results. Microcontrollers generally consume little energy to operate, allowing these devices to function for extended periods powered by batteries. By eliminating the need to transfer data to the cloud, the requirement for an internet connection and data transfer is eliminated, further reducing energy consumption. Some devices are used in environments where data privacy is paramount, and in these highly secure environments, internet connectivity may not be available to prevent data breaches. In such environments, only a device that performs local data processing can be utilized. This guarantees data integrity by ensuring that the data remains confined within the device and eliminates the necessity for external transfer and the potential dangers of their interception.

In order to achieve better classification accuracy, a new approach employed TinyML. An artificial neural network (ANN) algorithm was used with the assistance of the Edge Impulse platform to train a new model. The neural network architecture consists of an input layer composed of 78 features, followed by two hidden layers with 20 and 10 neurons, respectively, and an output layer with 5 neurons corresponding to each class. The model was trained to recognize the same five gestures as before. To train each gesture, a training of 10 sessions with 10 seconds per session was carried out, totaling 12 minutes and 10 seconds of data acquired in the training set. An additional 40 seconds of data for each gesture were acquired for model testing. The neural network model was trained using 50 epochs with a learning rate of 0.0005. After model training and cross-validation, a 100% accuracy and a loss of 0.05 were obtained, raising suspicions of overfitting due to the very high accuracy. Using the test set, the model was evaluated, resulting in a classification accuracy of 98.21%. Subsequently, the model was downloaded and executed on the Arduino board, with an estimated latency of 66 ms when deployed on real hardware. Evaluating the model on the Arduino board demonstrated a good gesture classification rate using real data from the IMU, indicating a good performance of the model.

IV. Limitations

The device can manage a wide range of intelligent building systems, being capable of associating gestures with various functions. However, limitations may arise regarding control and compatibility with certain systems that do not offer publicly accessible APIs or utilize older remote control or wired command systems that cannot connect to local or internet networks. To control these systems, it is necessary to retrofit devices that enable remote control through the internet.

Local processing of data from the IMU directly on the device enhances the device's level of data security and integrity. However, when a command is sent to a system, the security of the data relies on the type of protocol implemented by the API for transmitting data to the controlled equipment.

V. conclusion

This paper explores the use of smart clothing for controlling systems within a smart building. Gesture-based control assists individuals in interacting more easily with its systems, eliminating the need to physically approach a control panel or use other devices. A modularly designed prototype device was created for easy integration into garments, becoming an integral part of them. The created device was integrated into the sleeve of a garment to capture user gestures in the form of data from the IMU sensor. The IMU sensor available on the development board, in addition to providing acceleration and gyroscope data, also features an integrated Machine Learning Core capable of recognizing certain movements with low energy consumption. The Machine Learning Core utilized the decision trees method. Its capability was tested, but despite several attempts, the results were unsatisfactory for detecting the proposed gestures. To maintain the same user functionality, a new approach was adopted using TinyML. A fresh model was trained using an artificial neural network (ANN), resulting in an accuracy of 98.21% when evaluated with an independent dataset distinct from the one employed during training. The device integrated into the garment can operate independently of the internet. Gesture recognition is achieved using the computational power available onboard based on the locally stored model.

In the future, leveraging the possibilities offered by integration into clothing, multiple sensors could be employed to measure and suggest certain adjustments, such as detecting excessively low temperatures in the vicinity of the individual, identifying strong air currents, and recommending the closing of nearby windows, among others. The challenge of integrating multiple sensors is mostly the powering of the entire system. This can be improved by optimizing the system power consumption or using energy harvesting systems to charge the battery but requires future research in terms of benefits in relation to the added weight.

Acknowledgment

This work is supported by the NetZeRoCities Competence Center, funded by European Union–NextGenerationEU and Romanian Government, under the National Recovery and Resilience Plan for Romania, contract no.760007/30.12.2022 with the Romanian Ministry of Research, Innovation and Digitalization through the specific research project P3, Smart and sustainable buildings.

References

[1] "U.S.: smart home penetration rate 2019-2028," Statista. Accessed: Feb. 27, 2024. [Online]. Available: https://www.statista.com/forecasts/887639/penetration-rate-of-smart-homes-in-the-united-states

[2] D. S. Vijayan, A. L. Rose, S. Arvindan, J. Revathy, and C. Amuthadevi, "Automation systems in smart buildings: a review," *J. Ambient Intell. Humaniz. Comput.*, Nov. 2020, doi: 10.1007/s12652-020-02666-9.

[3] M. R. Reisinger, S. Prost, J. Schrammel, and P. Fröhlich, "User requirements for the design of smart homes: dimensions and goals," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, no. 12, pp. 15761–15780, Dec. 2023, doi: 10.1007/s12652-021-03651-6.

[4] Z. Li, J. Zhang, M. Li, J. Huang, and X. Wang, "A Review of Smart Design Based on Interactive Experience in Building Systems," *Sustainability*, vol. 12, no. 17, Art. no. 17, Jan. 2020, doi: 10.3390/su12176760.

[5] A. Rajabzadeh, A. R. Manashty, and Z. F. Jahromi, "A Mobile Application for Smart House Remote Control System." arXiv, Sep. 27, 2010. doi: 10.48550/arXiv.1009.5557.

[6] M. Kosanović and S. Stošović, "The concept for the 'Smart Home' controlled by a smartwatch," *Facta Univ. - Ser. Electron. Energ.*, vol. 31, no. 3, pp. 389–400, 2018.

[7] L. De Russis, D. Bonino, and F. Corno, "The smart home controller on your wrist," in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, in UbiComp '13 Adjunct. New York, NY, USA: Association for Computing Machinery, Sep. 2013, pp. 785–792. doi: 10.1145/2494091.2497319.

[8] R. Volety and P. Geethanjali, "Smart Home Automation Using Wearable Technology," in *Wearable/Personal Monitoring Devices Present to Future*, G. D. Gargiulo and G. R. Naik, Eds., Singapore: Springer, 2022, pp. 259–279. doi: 10.1007/978-981-16-5324-7_11.

[9] A.-V. Catană and R.-D. Vatavu, "Fingerhints: Understanding Users' Perceptions of and Preferences for On-Finger Kinesthetic Notifications," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, in CHI '23. New York, NY, USA: Association for Computing Machinery, Apr. 2023, pp. 1–17. doi: 10.1145/3544548.3581022.

[10] A.-V. Catană and R.-D. Vatavu, "Fingerhinter Takes Center Stage: User Experience Insights from Informal Encounters with a Finger-Augmentation Device," in *2024 IEEE International Conference on Artificial Intelligence and eXtended and Virtual Reality (AIxVR)*, Jan. 2024, pp. 265–269. doi: 10.1109/AIxVR59861.2024.00044.

[11] M. Weiser and J. S. Brown, "Designing Calm Technology".

[12] J. M. Collier, A. Wilkerson, D. Durmus, and E. Rodriguez-Feo Bermudez, "Studying Response to Light in Offices: A Literature Review and Pilot Study," *Buildings*, vol. 13, no. 2, Art. no. 2, Feb. 2023, doi: 10.3390/buildings13020471.

[13] T. Wang, R. Shao, and L. Hao, "Effects of Different Nocturnal Lighting Stimuli on Melatonin, Sleep and Cognitive Performance of Workers in Confined Spaces," *Buildings*, vol. 13, no. 8, Art. no. 8, Aug. 2023, doi: 10.3390/buildings13082112.

[14] A. Białek, L. Dębska, and N. Krawczyk, "Assessment of light intensity and productivity in the intelligent building – case study," *E3S Web Conf.*, vol. 336, p. 00011, 2022, doi: 10.1051/e3sconf/202233600011.

[15] "Nano RP2040 Connect | Arduino Documentation." Accessed: Mar. 06, 2024. [Online]. Available: https://docs.arduino.cc/hardware/nano-rp2040-connect/#features

[16] A. Industries, "OLED Breakout Board - 16-bit Color 1.5" w/microSD holder." Accessed: Mar. 06, 2024. [Online]. Available: https://www.adafruit.com/product/1431

[17] "Raspberry Pi Documentation - RP2040." Accessed: Mar. 11, 2024. [Online]. Available: https://www.raspberrypi.com/documentation/microcontrollers/rp2040.html

[18] "NINA-W10 series (open CPU)," u-blox. Accessed: Mar. 11, 2024. [Online]. Available: https://www.u-blox.com/en/product/nina-w10-series-open-cpu

[19] "Smart lighting," Philips Hue. Accessed: Mar. 15, 2024. [Online]. Available: https://www.philips-hue.com/en-us

[20] "LSM6DSOX - iNEMO inertial module with Machine Learning Core, Finite State Machine and advanced Digital Functions. Ultra-low power for battery operated IoT, Gaming, Wearable and Personal Electronics. - STMicroelectronics." Accessed: Mar. 11, 2024. [Online]. Available: https://www.st.com/en/mems-and-sensors/lsm6dsox.html

[21] "Unico-GUI - MEMS evaluation kit software package for Linux, Mac OSX and Windows - STMicroelectronics." Accessed: Mar. 11, 2024. [Online]. Available: https://www.st.com/en/development-tools/unico-gui.html

[22] "Weka 3 - Data Mining with Open Source Machine Learning Software in Java." Accessed: Mar. 11, 2024. [Online]. Available: https://www.cs.waikato.ac.nz/ml/weka/

[23] "About | tinyML Foundation." Accessed: Mar. 12, 2024. [Online]. Available: https://www.tinyml.org/about/