# Automation of Electronics Device Control Based on Human Activity with Weighted K-Nearest Neighbor Classification

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# AUTOMATION OF ELECTRONICS DEVICE CONTROL BASED ON HUMAN ACTIVITY WITH WEIGHTED K-NEAREST NEIGHBOR CLASSIFICATION

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## ABSTRACT

**Objective:** Human daily activities such as turn off/on the lights, the air conditioner, the music player, etc., require a lot of time. These activities can be electronically automated, using human activity recognition. This idea is based on the idea that rational agents seek goals to increase their wealth.

**Method:** In this research, it has been automated to turn on/off the light when someone passes through the road or stairs, turn on/off the air conditioner when someone is exercising, turn on/off the music player when someone is ironing clothes. The mechanization is done by using accelerometer and gyroscope sensors, to detect hand activities in these actions.

**Result:** The sensor output in the form of a signal will be classified using the weighted K-Nearest Neighbor algorithm, so the system can classify what movement is being done. The results of the classification will activate the electronic device according to the purpose for which it was designed. The classification accuracy obtained is 95%, so it can help reduce of daily routine activities.

**Conclusion:** The light switch used is a Smart Switch which is assembled using ESP-01 and a Relay, to turn off/on the switch. The Music Player used is coupled with WeMo's D1Mini and DF Player Mini, to activate and deactivate the Music Player. The Universal Remote is used to turn on/off the AC.


**Keywords:** activity, accelerometer, automation, classification, weighted k-nearest neighbor.

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# AUTOMAÇÃO DO CONTROLE DE DISPOSITIVOS ELETRÔNICOS COM BASE NA ATIVIDADE HUMANA COM CLASSIFICAÇÃO K-NEIGHBOR MAIS PRÓXIMO PONDERADA


## RESUMO

**Objetivo:** Atividades diárias humanas, como apagar/acender as luzes, o ar-condicionado, o player de música, etc., exigem muito tempo. Essas atividades podem ser automatizadas eletronicamente, usando o reconhecimento de atividades humanas. Essa ideia se baseia na ideia de que os agentes racionais buscam metas para aumentar sua riqueza.

**Método:** Nesta pesquisa, foi automatizado para ligar / desligar a luz quando alguém passa pela estrada ou escadas, ligar / desligar o ar condicionado quando alguém está se exercitando, ligar / desligar o leitor de música quando alguém está passando roupas. A mecanização é feita com o uso de sensores de acelerômetro e giroscópio, para detectar atividades manuais nessas ações.

**Resultado:** A saída do sensor na forma de um sinal será classificada usando o algoritmo K-Nearest Neighbor ponderado, para que o sistema possa classificar qual movimento está sendo feito. Os resultados da classificação acionarão o dispositivo eletrônico de acordo com a finalidade para a qual foi projetado. A precisão de classificação obtida é de 95%, o que pode ajudar a reduzir as atividades rotineiras diárias.

**Conclusão:** O interruptor de luz usado é um interruptor inteligente que é montado usando ESP-01 e um relé, para desligar / ligar o interruptor. O Music Player usado é combinado com o D1Mini da WeMo e o DF Player Mini, para ativar e desativar o Music Player. O Universal Remote é usado para ligar/desligar a CA.


**Palavras-chave:** atividade, acelerômetro, automação, classificação, k-vizinho mais próximo ponderado.

## 1 INTRODUCTION

Daily routine activities carried out by humans at home spend a lot of time because they are done repeatedly. This can be overcome by applying the concept of automation. Automation will reduce human work, helping seniors who have difficulty moving or are physically disabled. Machine learning will be used to classify human activities, so that it can be determined what type of automation will be carried out by electronic devices.

In this study, the Weighted K-Nearest Neighbor (WKNN) is used as a classifier of daily movements. The WKNN algorithm is a closest neighbor classification model that can be determined by distance metrics and number of nearest neighbors. Since the KNN classification preserves training data, training data can be used as a classification model for new inputs.

In this study, automation was applied when someone was walking the light would turn on, when someone was going up or down the stairs the light would turn on, when someone was exercising the fan would turn on, when someone was ironing the music would be sung. The use of accelerometer sensors and gyroscope sensors will help detect a person's body movements. The sensor output signal will be entered into the WKNN classifier and the classification output will be used to turn on or turn off electronic devices.

The remains of this document is organized by the subsequent units: Unit 2 briefly presents an summary of the WKNN classification. Unit 3 defines the electrical devices used. Unit 4 provides experimental outcomes. Unit 5 concludes the document.

## 2 LITERATURE REVIEW

Engine knowledge approaches have been used in changed fields, there are numerous approaches of machine learning, such as audited learning, unverified knowledge and reinforcement knowledge. In audited learning, the concept of teacher or supervisor may be similar to that of the teacher or supervisor, and its primary function is to provide the agent with the appropriate measure of error. Training data is the expected input and output pairs. Based on that information, the agent can refine its parameters to reduce the magnitude of the overall loss function. If after an inversion the algorithm is quite elastic and the data basics are solid, the overall accuracy rises and the change among the projected and probable values approaches zero. The target is to monitor a system that works with never-before-seen data. This is essential for the development of generalizations and to avoid a common problem called surplus. In unaudited learning they are not supervised, so total errors are made. This is useful for collecting data based on similarities (or calculated based on a distance measurement).

In addition, reinforcement is not a true supervisor when it comes to learning, but is based on the learning environment. However, in this case, the information is more qualitative and does not help the agent determine the exact size of the error. When reinforcing learning, this response, in general, is called reward (sometimes defined as negative punishment) and is useful to understand if a particular action was performed in a positive situation. The most useful actions are the principles that agents must learn to make the best decisions based on the fairest and most collective awards. In other words, an action may be incomplete, but in the case of global politics it must give the highest prize. This idea is based on the idea that rational agents seek goals to increase their wealth. Visual ability in remote horizons is a characteristic feature of experienced agents, while myopes are often not able to adequately assess the effects of their immediate activity, so their strategies are not adequate (Bonaccorso, 2017).

There are three types of problems in machine learning, which are binary arrangement (Kumari & Kr., 2017), multiclass classification (Alsafy et al., 2014), and scalar regression (Reiss et al., 2010).

Binary formats based on decision tree algorithms have been used in distributed environments with big data. Data is stored in the cloud, so virtual resources are scalable, provide a knowledge base for decision-making, and are suitable for managing a growing volume of data. It was found that chance forest trees made best among the three algorithms for the data set under consideration. Organization approaches such as conclusion trees, ramp boasted trees, and chance forest trees were compared to assess their presentation based on specific limitations. It was found that casual woodland trees performed finest between the three processes for the dataset under consideration (Naik & Purohit, 2017).

In machine learning, multiclass classification creates a series of predictions for users to choose this option, with specific perspectives, to choose the option that best suits them. The goal of using multiclass in medicine is to develop a decision support system that can be interpreted using machine learning to support physicians. Research data has a 58% success rate, as a consequence of various imbalances and overlapping classes in real-world application data. This indicates the need for further validation in clinical samples (J. Zhang et al., 2013). Reversion scaling for the detection and documentation of cancer bio producers (Liu et al., 2020).

Human action sensing is an establishment of methods that can be used in multiple requests, with smart homes and healthcare. This article discusses the identification of activities around the smart home, especially the identification of the entrance to the home and the exit of a room from the home or office. This data can be used in HVAC (heating, ventilation and air conditioning) and light requests or in environmental applications that monitor community well-being (AAL). From our perspective, we use information from two common instruments, a inactive infrared (PIR) sensor, which will monitor the presence by opening or closing the door, and one is the impact sensor. Installation is prudent and relatively straightforward, as the sensor nodes connected to the sensors are battery-motorised and not an additional task to ensure power supply requirements. Two methods of detecting activity are proposed, one based on opaque windows and another based on artificial neural networks. (ARNA). The algorithm was verified in datasets collected in a laboratory setting (Skocir et al., 2016).

The number of physical strategies linked to the Internet has increased rapidly and the development of Internet of Things applications that can improve your value of life has accelerated. It is probable that by the end of 2020, 20,000 million connected devices will be connected to 6,400 million connected in 2016. Applications using connected devices can be divided into three broad areas: the industrial field, the smart city domain and the preponderance of health and fitness. Smart homes, as part of the smart city assumption, are often cited in IoT-focused surveys. By connecting a thermostat device to the Internet, a home automation system allows remote control of the HVAC system via a web or mobile application. In addition, smart grid devices can optimize energy consumption, as they have created a schedule for appliances to operate at a slower speed. (Palaniappan et al., 2015). Some apps allow for more advanced capabilities, like regulatory devices based on the user's place. For sample, it turns on the boiler when the user goes home.

It produces more than 70 million units a year and motorized manufacturing is one of the largest industrial trades in the world. According to global calculations, the global revenue of the automotive industry is 3 trillion, accounting for 3.65% of global GDP (Garay et al., 2022). The presence of IoT in the automotive sector has shaped new occasions for car manufacturers and buyers around the world. With industrial and commercial applications, IoT has become an important access to the automotive industry for multiple flexible requests. From connected cars to automatic transport schemes, Internet of Things requests are having a important influence on automotive companies around the world. The Internet of Effects, along with other disruptive facts, is reforming the automotive sector. The development of this sector has led to revolutionary advances in automobiles, that is, in vehicles and independent vehicles. The changed kinds of Internets of Things technologies have important characteristics and make them viable as a skill for use in the motorized trade. This paper builds on discoveries made by previous researchers on the Internet and describes how the technology works. (Beg et al., 2022).

Lora (remote) is critical to completing intelligent solutions in the Internet of Effects (IoT). Home mechanization is answerable for providing a protected and fashionable home. This document suggests a solid home automation construction for communication technologies in the short and long term, i.e. Lorawa, Lora Gateway, Bluetooth and connectivity. This combined classification effectively controls various kinds of household appliances and maintains intelligent organization among all electronic components. Normal users can easily manage this harmonized system via the Android app. This article also presents an analysis of the research information. The outcomes and argument chapters offer experiments such as the calculation of transmission mirror estimates for LORA, Wi-Fi and Bluetooth, the calculation of the coverage part for FLOOR with RSSI and SNR values and the System Utility Scale (SUS). This organization has obtained a ranking of 93%. Though, the future architectural package is straightforward for the smart home and will be highly applicable, varied and useful(Islam et al., 2021).

## 3 RESEARCH METHODS

### 3.1 K-NEAREST NEIGHBORS

K-Nearest Neighbors (KNN) It's a simple machine learning method. The basic idea of the KNN algorithm is discussed here. The dataset is prepared before fulfilling the KNN function (CNN). Once the expected results have been obtained with the KNN algorithm, the analytic presentation of the model must be check. The regular accurateness is used to reflect the KNN algorithm. Factors such as the k-value, the calculation of the distance and the choice of the appropriate preacher meaningfully effect the performance of the model (Z. Zhang, 2016).

The KNN classifier is used to categorize unlabeled explanations by categorizing them into categories from the most similarly labeled examples. Observational features were collected for training and test datasets. For example, fruits, vegetables, and grains can be distinguished by their squeakiness and sweetness. To display it on a two-dimensional plane, only two features are used. The truth is that there are some predictions and the example can be augmented to introduce any feature. In some, fruits are sweeter than vegetables. Grains are not crunchy or sweet. In testing sweet potatoes will be determined including groups of fruit, vegetables or grains. In this example the four closest foods are selected, they are apples, green beans, lettuce, and corn. Since vegetables won the most votes, sweet potatoes were grouped into vegetables. It can be seen that the KNN key concept is easy to appreciate.

There are two main ideas in the example above. It is a way of calculating the distance among one of them and extra types of food. First, the KNN() function uses the Euclidean distance that can be calculated using the following equation (Z. Zhang, 2016).

$$D(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \qquad (1)$$

Where,

p and q are subjects to be associated with N features. One more thought is the k parameter, which concludes how many neighbors they choose for the KNN algorithm. The direct choice of CNN effects the indicative presentation of the KNN algorithm. A large K decreases the influence of variation caused by a casual defect, but the danger that it is not a small but significant design. The key to choosing the right K value is to strike a balance between surplus and infrared. Some authors advise that the amount of observations in the k-training dataset is equal to the square root. (Z. Zhang, 2016).

The following is the explanation of KNN (Bicego & Loog, 2016):

• x: is something to be classified;

•{xi} (dengan $1 \leq i \leq N$): The N-points team in the training team; Each training model has a label {yi} (with $1 \leq i \leq N$). The label yi can be one of the possible values 1 . . . C, where C is the number of classes of the problem encountered.

• $ne_K(x) = \{n_1, ..., n_K\}$: K-points on the training equipment closest to x, from a given distance d(•, •); $yn_1, ...yn_K$ are the corresponding labels; please note that we consider $\{n_1, ..., n_K\}$ as ordered according to the distance from x — $n_1$ is the nearest neighbor, $n_K$ is the farthest of the K nearest neighbors.

Given these meanings, the standard KNN rule assigns x to the class cˆ more frequent in the set $ne_K(x)$, i.e (Bicego & Loog, 2016).

$$x \leftarrow arg\ arg\ \left|\{n_i : y_{n_i} = c\}\right| \qquad (2)$$

Where,

X| denotes the cardinality of the set X. Rule (1) can be rewritten as (Bicego & Loog, 2016).

$$x \leftarrow arg\ arg\ [\textstyle\sum_{i=1}^{K} \quad I_c(n_i)] \qquad (3)$$

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Where,

$I_c(u)$ is the indicator function for class c (Bicego & Loog, 2016).

$$I_c(u) = \{1\ if\ u\ belongs\ to\ class\ c \quad 0\ otherwise \qquad (4)$$

1

The summation in (2), for a given c, Only the number of points between neighbors counts $ne_K(x)$ belonging to class c.

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## 3.2 WEIGHTED K-NEAREST NEIGHBOR

K-Nearest Neighbor (KNN) these values are easily used and classified for your application. This gives X points in class K on physical activity equipment closest to point X. To control one of the adjacent points, this is done by calculating the distance. Here, all the surrounding points also support X's final decision. Therefore, to improve performance, the weight is updated.

In a classification setting, (Gou et al., 2012) the KNN and distance-weighted rules provide acceptable empirical evidence. He discusses several alternatives for determining weights, all weights discarded with respect to X - 1 for the first nearest neighbor and a floor of 0 of k. Taking into account the weights, each neighbor helps with his weight in the final decision: in particular, the Weighted K-Nearest Neighbor (WKNN) standard gives the class X that has a representative weight among the number of K nearest neighbors to be the largest value (Bicego & Loog, 2016).

Within the nearest neighbor norm to the weighted K, each neighbor does not have a weighted wni ∈, and can be calculated, for example, using the methods presented. Keep in mind that in the general configuration we can have a dissimilar weight group for each point to be classified: when changing the point x to be classified, the neK( x) It also changes, so the corresponding weight directly depend on the association among the neighbors and point X.. This is clear, for example, when taking into account the meaning of the weights entered into the equation. (2) of [13]:

$$w_{n_i} = \frac{1}{d(x,n_i)} \qquad (5)$$

With this explanation, the weight of a certain training model is changed to be classified when point X changes: it depends on the distance X from this point: the farther away the neighbor is, the greater weight/north it will have in the organization of X. This meaning of weights is based on typical ideas of the Parzen Windows estimator (Bailey & Jain, 1978). Given neighbors and weights, the Weighted K-nearest neighbor rule assigns x to the class cˆ for which the weights of its governments in the neighborhood ne(x) sum to the highest value. Following the notation of Equation (2),

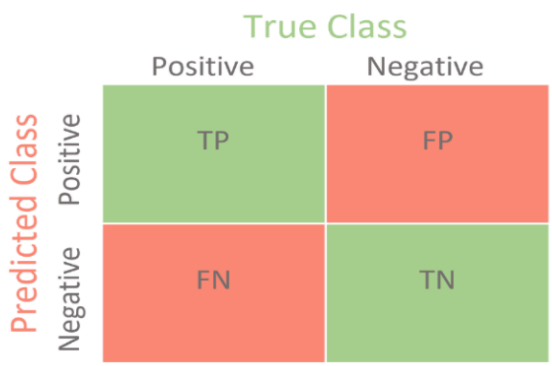
$$x \leftarrow arg\ arg \left[\sum_{i=1}^{K} \quad I_c(n_i) w_{n_i}\right] \qquad (6)$$

Clearly, the KNN and the Weighted KNN rules are equivalent when K=1.

3.3 DIAGNOSTIC MODEL PERFORMANCE

The misperception matrix is a table to describe the prediction model presentation of a process knowledge model. Each entry in the confusion matrix shows the number of calculations produced by the model, whether the model correctly or wrongly classifies the classes. Figure 1 is a confusion matrix for binary arrangement.

Figure 1. Confusion Matrix Binary Classification.




Source: Prepared By The Author, (2023).

As you can see, there are only two classes to classify the binary classification problem, especially one positive and one negative class. Now let's look at the matrix of the confusion matrix.

Real positive (TP): Corresponds to the number of predictions that the classifier accurately preaches the positive class. True negative (TN): Classification refers to the number of predictions that accurately preach the negative class as negative. False positive (FP): Corresponds to the number of predictions that the classifier directly preaches as positive the negative class. False negative (FN): Corresponds to the number of predictions that the classifier directly preaches as negative the positive class.

It is always better to use the confusion metric as an assessment principle for machine learning models. It measures a very simple but effective presentation for your accuracy. Here are some common representation verbs that you can use from the confusion matrix (Tolkachev et al., 2023).

Detail: This gives you a general accuracy of the model, i.e. the fraction of all samples correctly classified by the classifier. To calculate the accuracy, use the following formula: (TP+TN)/(TP+TN+FP+FN).

1. **The misclassification rate:** tells you what wrong part the predictions were. It is also known as a classification error. You can calculate using (FP+FN)/(TP+TN+FP+FN) or (1-Accuracy).
2. **Precision:** It tells you how many positives your predictions were as a positive class. To calculate the accuracy, use the following formula: TP/(TP+FP).
3. **Recall:** It tells you which part of all positive examples was correctly predicted as positive by the classifier. It is also known as True Positive Rate (TPR), Sensitivity, Possibility of Discovery. To calculate Recall, use the following formula: TP/(TP+FN).
4. **Specificity:** It tells you that a portion of all negative samples are established as negative based on the format. It is also known as a True Negative Rate. (TNR). To calculate specificity, use the following formula: TN/(TN+FP).
5. **F1-score:** It combines precision and recall in a measurement. Mathematically, it is a harmonic environment of precision and recall. It can be calculated as follows:

$$F_1\text{−score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \quad (7)$$

Now, in a complete Earth, we would like a model with accuracy of 1 and memory of 1. This means the F1 score of 1, i.e. 100% accuracy, which is often not the case for a machine learning model. Then you have to try to get higher accuracy, with a advanced recovery value.

### 3.4 ELECTRONIC DEVICES

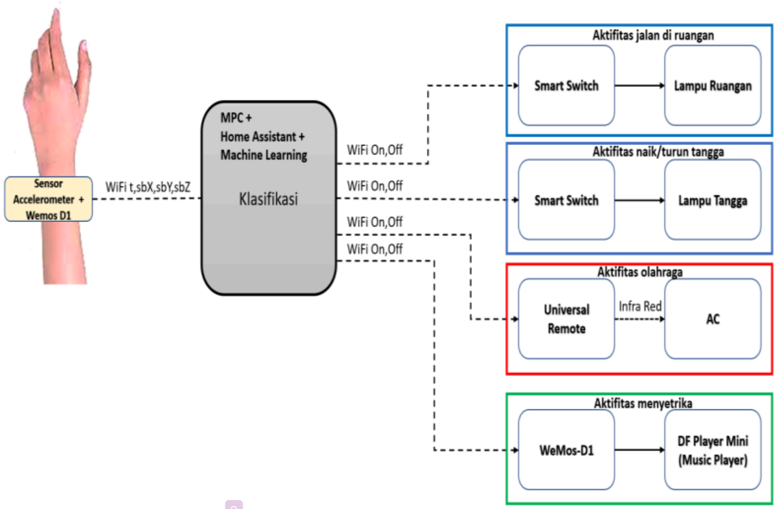
Electronic devices designed using the MPU-6050 is an accelerometer and gyroscope sensor, which will be used as input to devices based on human activity. Based on different movement data, human activities will be classified, and then classification results will activate the device via a WIFI network. The block diagram of devices system can be seen in Figure 1.

The accelerometer sensors in the hand sensor above t, aX, aY, and aZ data (time, X acceleration, Y acceleration, and Z acceleration) and the gyroscope sensors X, Y, Z are processed with WeMos D1 Mini, and then send it to the minicomputer (MPC) using WiFi communication. The data received by the computer is used to classify the activities being carried out at that time. After the computer gets the classification results, the classification results are sent using WiFi communication to the intended devices according to their activities.

There are four electronic devices that can be adjusted, namely: room light switches, stair lights, air conditioning, and a music player. All of these electronic devices are controlled through software in the Mini PC, in order to set the automation desired by the user. The light switch used is a Smart Switch which is assembled using ESP-01 and a Relay. To turn off and turn on the switch, user only need to give the On or Off command.

The Music Player used is assembled with WeMos D1Mini and DF Player Mini, to activate and deactivate the Music Player, simply give the On or Off command. The Universal Remote that is used is only the On/Off function to turn on/off the air conditioning.

Figure 2. Block Diagram System Introduction To Activity Movement.

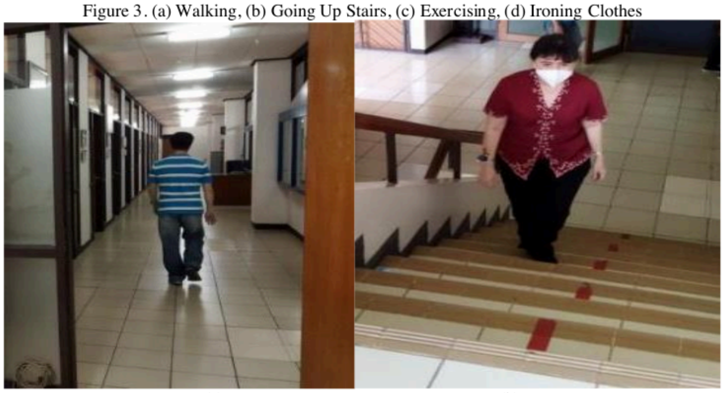



Source: Prepared By The Author, (2023).

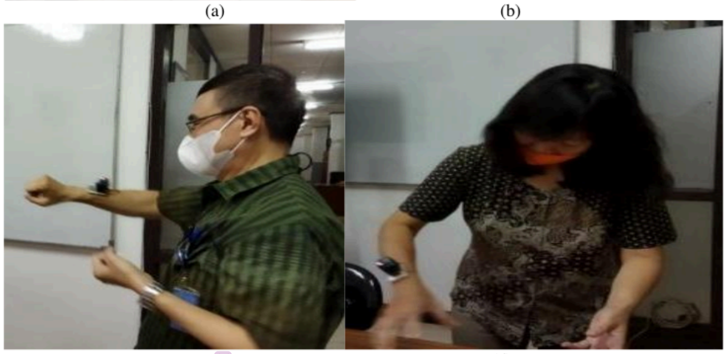
## 4 RESULTS AND DISCUSSION

Experimental data for each participant is 150 data. There are 10 respondents, so there are 1500 data. The four activities that are often carried out daily are walking, going up/down stairs, exercising, and ironing clothes, can be shown in image 3.

Figure 3. (a) Walking, (b) Going Up Stairs, (c) Exercising, (d) Ironing Clothes



(a) (b)



(c) (d)

Source: Prepared By The Author, (2023).

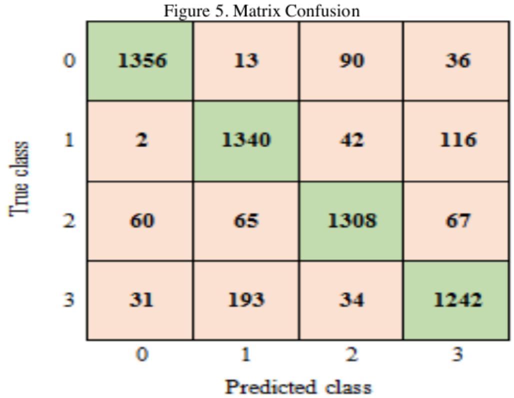
The device designed to receive accelerometer sensor input signals X, Y, Z, and gyroscope; can be seen in Figure 4. The received signals are classified with WKNN with multiclass outputs of walking, going up/down stairs, exercising, and ironing clothes.

Figure 4. Design tools

Source: Prepared By The Author, (2023).

The resulting confusion matrix can be seen in Figure 5.

Figure 5. Matrix Confusion



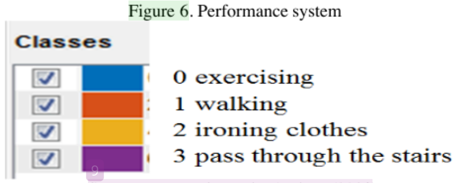

Source: Prepared By The Author, (2023).

Table 1. Performance system

| Class | Accuracy | Precision | Recall | Specificity | FL-score |
|---|---|---|---|---|---|
| 0 | 0.96 | 0.91 | 0.94 | 0.96 | 0.92 |
| 1 | 0.99 | 0.89 | 0.83 | 0.96 | 0.86 |
| 2 | 0.93 | 0.87 | 0.88 | 0.95 | 0.87 |
| 3 | 0.92 | 0.82 | 0.85 | 0.94 | 0.83 |
| Average | 0.95 | 0.87 | 0.87 | 0.95 | 0.87 |

Source: Prepared By The Author, (2023).

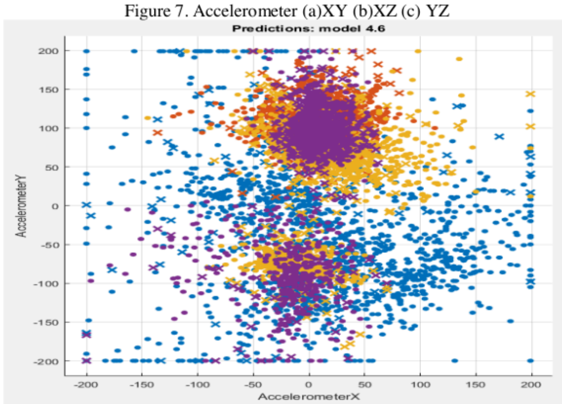
Figure 6. Performance system



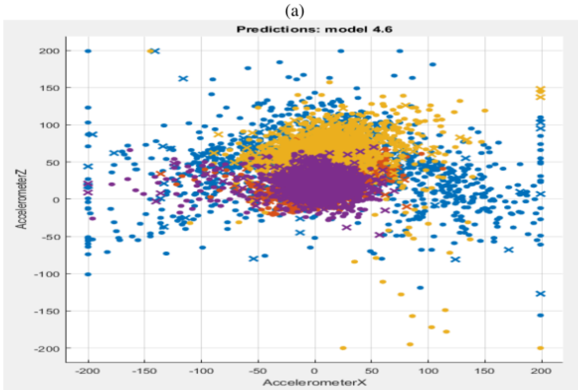

Source: Prepared By The Author, (2023).

Scatter plots of the accelerometer sensor on the X and Y axes, X and Z axes, Y and Z axes.

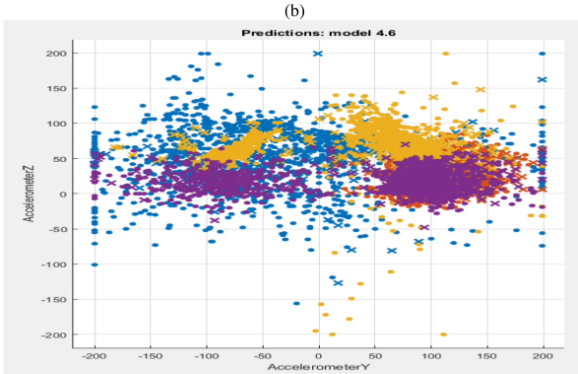
Figure 7. Accelerometer (a)XY (b)XZ (c) YZ




(a)




(b)

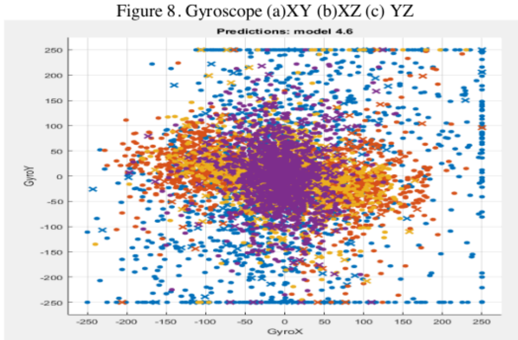



(c)

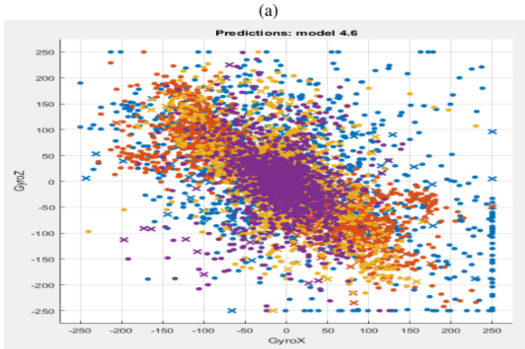
Source: Prepared By The Author, (2023).

Scatter plots of the gyroscope sensor on the X and Y axes, X and Z axes, Y and Z axes.

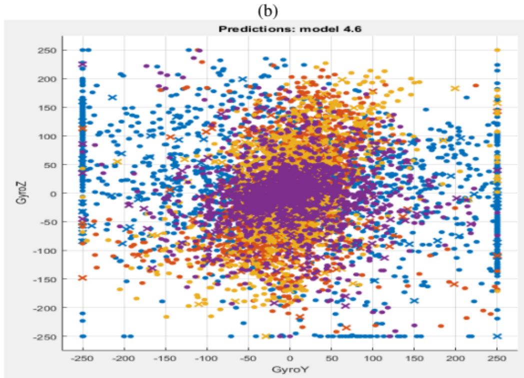
Figure 8. Gyroscope (a)XY (b)XZ (c) YZ




(a)




(b)




(c)

Source: Prepared By The Author, (2023).

## 5 CONCLUSION AND SUGGESTION

Automation can be implemented using the MPU-6050, which is an accelerometer and gyroscope sensor to detect four activities, namely turning on/off the lights when someone going up/down stairs, turning on/off the music player when someone is ironing clothes, turning on/off the air conditioner when someone is exercising. Classification results using the weighted K-Nearest Neighbor are : average accuracy of 0.95; precision 0.87; recall 0.87, specificity 0.95 and F1-score 0.87. After the computer gets the classification results, and then sent the data using WIFI communication to the intended devices according to their activities. There are four electronic devices that can be adjusted, namely: room light switches, stair lights, air conditioning, and a music player. All of this electronic equipment are controlled through software that resides in the Mini PC in order to set the automation desired by the user. The light switch used is a Smart Switch which is assembled using ESP-01 and a Relay, to turn off/on the switch. The Music Player used is coupled with WeMo's D1Mini and DF Player Mini, to activate and deactivate the Music Player. The Universal Remote is used to turn on/off the AC.

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