ICIC Express Letters ICIC International ©2022 ISSN 1881-803X
Volume **16**, Number **1**, January **2022** pp. **91–100**

AN EVALUATION OF ACTIVITY RECOGNITION WITH HIERARCHICAL HIDDEN MARKOV MODEL AND OTHER METHODS FOR SMART LIGHTING IN OFFICE BUILDINGS

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Received March 2021; accepted June 2021

Abstract. *If the software developed to automatically turn off lights on a smart lighting solution installed in office buildings is not good, the problem that arises is user complaints, because the lights can turn off even though the equipped Passive Infrared (PIR) sensor has detected user movement. A Hierarchical Hidden Markov Model (HHMM) method applied to Activity Recognition (AR) can be used as a solution to predict activity from PIR sensor data and predict the lighting mode from activity. The purpose of this study is to apply HHMM and compare its performance with other machine learning methods, namely KNN, Naïve Bayes, and HMM which can be used for AR in smart lighting in office buildings. An Internet of Things (IoT) system is built to collect data and then form a machine learning model for comparison. The HHMM method is proven to be superior to other methods, which has an accuracy of 87.6%.*
Keywords: Activity recognition, Smart lighting, HHMM, KNN, Naïve Bayes, Internet of Things, PIR sensor

1. **Introduction.** Many companies comply with the 7th Sustainable Development Goal (SDG) set by the United Nations Organization (UNO) on energy saving [1-3]. A solution that can be applied is green building, which is a building that utilizes renewable energy and energy-efficient LED lighting [4,5]. The application of smart lighting can be added to the solution because it provides savings of up to 25% compared to conventional lighting [6-10].

In terms of achieving efficiency, usually smart lighting adjusts light intensity to outside light or turns off the lights when no one is around by utilizing Passive Infrared (PIR) sensors [11]. However, if the software developed to turn off the lights automatically is not well developed, the problem that arises is user complaints, because the lights can turn off even though the user is present [12]. Activity Recognition (AR) can be used as a solution, which is a method for predicting user activity through sensors planted in a room, house, or building [13]. Prediction methods with machine learning such as K-Nearest Neighbor (KNN) and Naïve Bayes can be used in AR [14-16]. However, the sequential nature of the Passive Infrared (PIR) sensor data and the hierarchical prediction type make the Hierarchical Hidden Markov Model (HHMM) a more suitable choice. HHMM is an extension of the Hidden Markov Model (HMM) which deals with complex and hierarchical data dependencies [17-19].

The purpose of this study is to apply HHMM and compare its performance with other machine learning methods that can be used for AR in smart lighting in office buildings.

DOI: 10.24507/icicel.16.01.91

To achieve this goal, an Internet of Things (IoT) system was built to collect data [20]. The data collected on an IoT platform in the system is then used to create machine learning models for HHMM, KNN, and Naïve Bayes. These methods are then compared in performance. So the performance comparison as the outcome of this study can be used as a reference in determining a machine learning model to predict the right lighting mode in a room based on activity or movement.

The systematics of this paper organization is as follows. Chapter 2 contains related works. Chapter 3 contains system design. Chapter 4 consists of system implementation, comparison of the performance of the methods used, and discussion. Chapter 5 contains the conclusions of the research.

2. **Related Works.** Smart lighting is a research that continues to develop with a focus on various aspects. A study in 2017 introduced the Internet of Underground Things, or IoUT, which is applied to smart lighting [21]. A study in 2018 examined the comparison of energy consumption on various savings strategies [22]. A smart lighting study in 2020 tested the network performance of smart lighting, especially on variations in signal strength, network protocol, and number of users [23].

HHMM is an extension of HMM for prediction models on stratified sequential data and can be used in various fields. In the medical field, a study in 2017 utilized the first level of the HHMM to use the raw information to predict nucleosome information, then use nucleosome information to predict domain information [24]. In the field of psychology, a study in 2020 applied the first level of HHMM to using psychological response time tests to predict response modes and use response mode data to predict the environment [25]. In the field of meteorology, a study in 2021 utilizes the first layer of HHMM to predict wind speed, while the second layer is used to classify the type of wind [26].

AR is a prediction of activity using machine learning methods. A study in 2016 raised the problem of predicting activity from non-wearable sensors and offered a solution called state thresholding framework [27]. A research in 2019 focused on the feature extraction method, namely the Term Frequency-Inverse Document Frequency (TF-IDF) method [28]. A study in 2020 used 6 different variations of the Hidden Markov Model (HMM) plus one ensemble learning of the six variations for AR [29]. In 2021 there is research on AR that proves that distributed connectivity can improve the response time of AR [30].

In Table 1, a comparison of all the studies discussed in this chapter with the research proposed in this paper can be seen. What motivates this research based on the related studies that have been studied is for effective smart lighting control, which has not been studied from other smart lighting studies. In this case, HHMM can be used, because the smart lighting that will be developed has multilevel learning from sensors to activities, then from activity to light mode. Meanwhile, from related research on AR, there is no research that discusses the implementation of smart lighting with HHMM in particular.

Table 1. AR smart lighting system comparison

Reference	Smart lighting	Application of HHMM	Activity recognition
[21-23]	Yes	No	No
[24-26]	No	Yes	No
[27-30]	No	No	Yes
Proposed system	**Yes**	**Yes**	**Yes**

3. System Design.

3.1. Smart lighting design. In the smart lighting process, the first thing that is done is the machine learning process. There are 3 data entered into the machine learning system, namely activity or movement data that is reached by the motion sensor, lux data around the lamp device, and the identity of the lamp. Then this input data will be sent to the server for further processing. The machine learning algorithm will run after the input data is received by the server. The data flow between the sensor device, the light system, and the server can be seen in Figure 1.

The system is implemented in a part of an office building; specifically, it is placed in the IT Division Workspace. Figure 2 explains the office layout, the sensor placements, the lights placements, and the zones. Zone 1, Zone 2, and Zone 3 represent the IT Room,

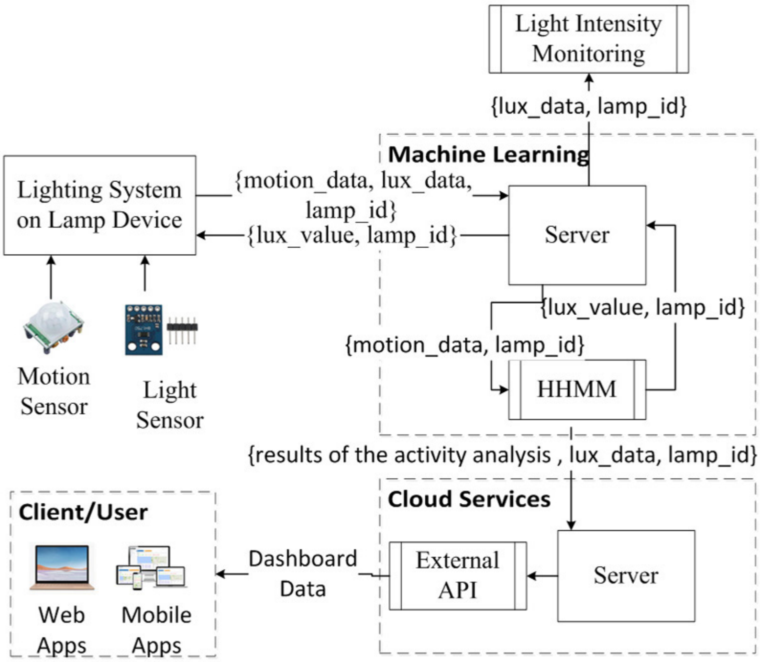


FIGURE 1. Smart lighting system design

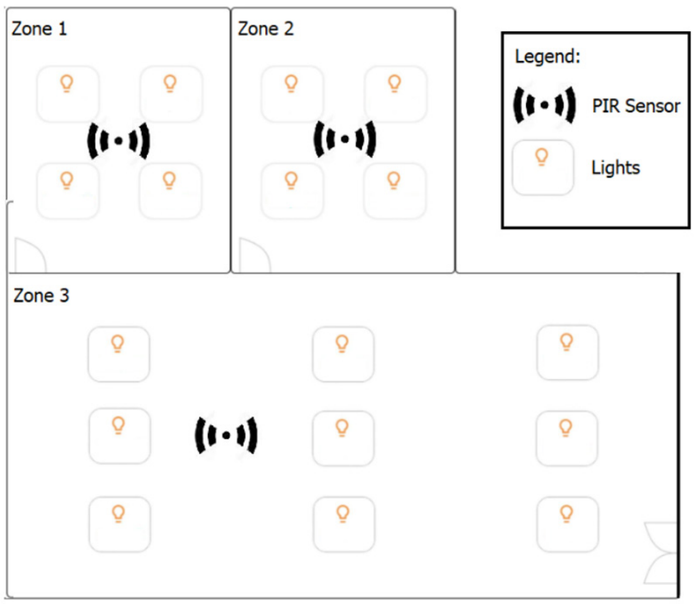


FIGURE 2. Office layout

the Archive Room, and the Recreation Room, respectively. These zones will be used in HHMM model explained in the next subchapter.

3.2. **Activity recognition with hierarchical hidden Markov model.** There are five activities used in this study. The five activities are work initiation, room checking activities, reporting activities, IT data backup activities, and resting activities. Meanwhile, there are three rooms used in this study. The names of these rooms are the archive room, IT office, and rest room. In Table 2, the mapping of lighting modes to activities can be seen. The names used for the three lighting modes are low mode, medium mode, and high mode.

TABLE 2. Lighting mode vs activities

Lighting mode	Activities
Low	Resting
Medium	Work initiation
	Room checking
High	IT data backup
	Reporting

The method used for activity detection in this study is HHMM. The HHMM model is a two-stage extension of the HMM model where the HHMM has two levels higher. Figure 3 is a detailed explanation of the HHMM structure. T is the first level hidden state, N is the number of states at the first level, R is the observation state, M is the observation symbol number (item), P is the second level hidden state, and K is the number of states at the second level. Transitions between nodes will be calculated as the probability of displacement.

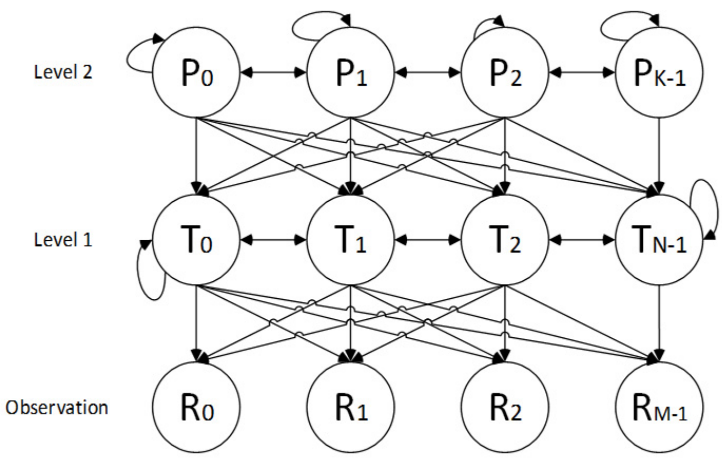


FIGURE 3. Hierarchical hidden Markov model

In this study, the HHMM structure to be used is shown in Figure 4. The figure explains, among others, the initial state used for the initial probability value, the emission probability between the zone and the activity, and the transition probability between activity to activity.

After implementing the HHMM model, the identification of the existing hidden states is carried out using the Viterbi algorithm. The first step is seen in the following equation.

$$\delta t(i) = \max_{q_1,q_2,\ldots,q_{t-1}} P\left[\begin{array}{c} q_1, q_2, \ldots, q_{t-1}, q_{t=i}, \\ o_1, o_2, \ldots, o_t \end{array} \middle| \lambda \right] \tag{1}$$

where $\delta t(i)$ is the best series, $q(i)$ is the hidden series, $o(i)$ is the observable series, and given the automaton λ.

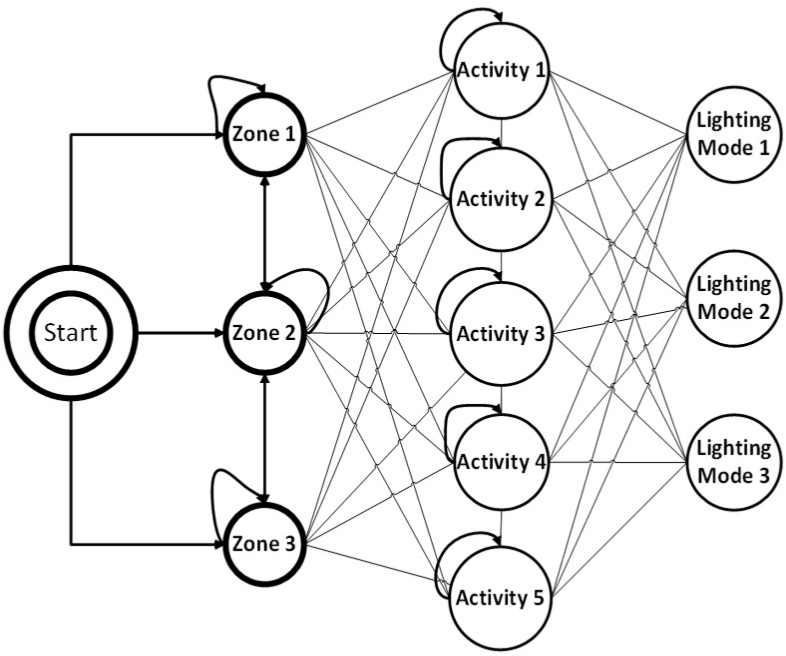


FIGURE 4. The HHMM model for the smart lighting activity recognition

The calculation follows several steps, namely initialization, recursion, termination, and path status. The following equation is the initialization stage.

$$\delta 1(i) = \Pi_i b_i(o_1), \quad 1 \leq i \geq N \tag{2}$$

where Π_i is equal to the initial probability, $b_i(o_1)$ is equal to the first element of state observation's probability output. $1 \leq i \geq N$ is a range where i is the state and N is the number of states.

$$A\gamma(1) = 0 \tag{3}$$

where $A\gamma(1)$ is set to 0 and is equal to the first transition probability value.

In the recursive stage, a repetition process is carried out on the process itself with the following equation.

$$\delta t(i) = \max[\delta t - 1(i) a_{ij}] b_j(o_t) \text{ for } 1 \leq i \leq N \tag{4}$$

where $\delta t - 1(i)$ is the last time in the time series with the state i. a_{ij} is the transition probability from i to j while $b_j(o_t)$ is a state that is equal to the density probability.

In the termination stage, the following equation is executed.

$$P^* = \max[\delta t(i)] \text{ for } 1 \leq i \leq N \tag{5}$$

where P^* is the decision stage carried out. It is determined from the maximum value of $\delta t(i)$ which is the observation sequence value.

The status path state determines the final output. After the activity path is generated, the next process is to calculate the suitability between the activity path and the light mode that will be produced.

$$LM[i] = P^*[i] \text{ for } 1 \leq i \leq P^* \tag{6}$$

where $LM[i]$ is the condition of the ith lamp mode which will be calculated according to the length of the activity line output.

4. Evaluation.

4.1. System implementation.

Based on the design described earlier, several mock-ups of the application were made so that users could access them from the public. An example of an application mock-up can be seen in Figure 5.

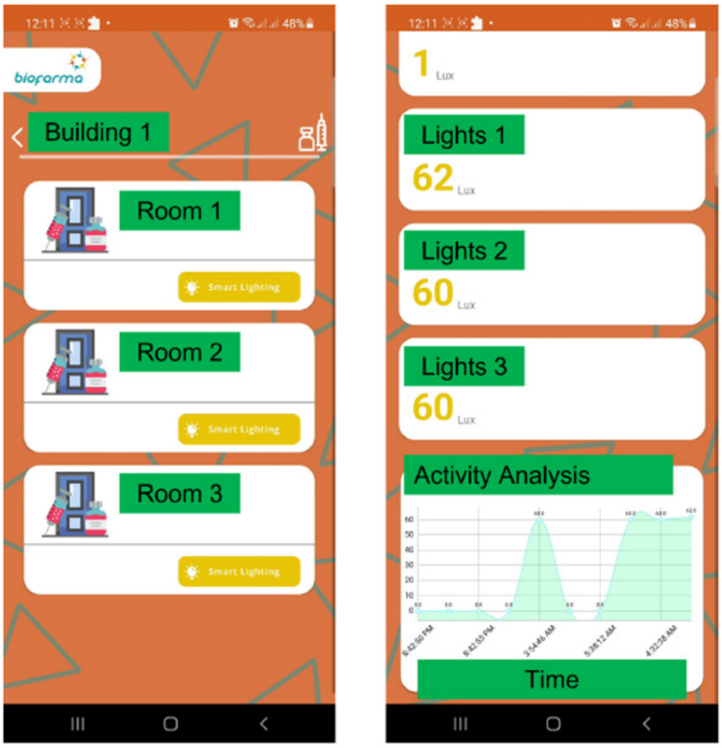


FIGURE 5. Application mock-up

4.2. **HHMM implementation and performance comparison.** The matrix that explains the transition from activity to activity in the HHMM can be seen in Figure 6. There are five activities, as mentioned in Table 2, interacting with each other. The matrix is served in forms of a heatmap to ease the viewers to see which interactions have high probability and which interactions have low probability.

The matrix that explains the transition from lighting mode to lighting mode can be seen in Figure 7. There are three lighting modes, as mentioned in Table 2, interacting with each other. The matrix is served in forms of a heatmap to ease the viewers to see which interactions have high probability and which interactions have low probability.

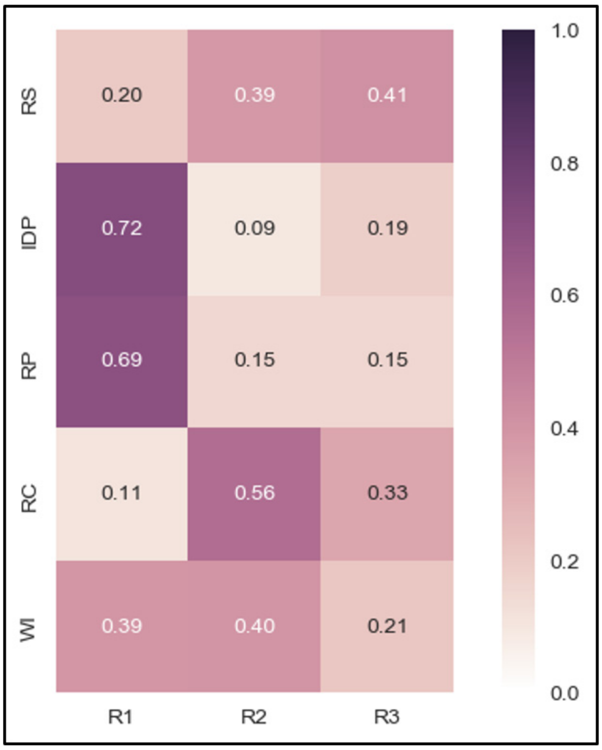
To measure the performance of the HHMM model performance, several measuring metrics are used, namely accuracy, precision, recall, and f1-score. The performance of the HHMM lighting mode prediction can be seen in Figure 8. The lowest overall performance is provided by the low mode. The highest overall performance is provided by the high mode.

Furthermore, a comparison is made between HHMM and other machine learning methods, namely HMM, Naïve Bayes, and KNN. The comparison results can be seen in the bar chart in Figure 9. Three highest score of all performance metrics comes from HHMM. Two lowest score of all performance comes from HMM. Naïve Bayes provides the highest recall but the lowest precision. KNN provides the lowest accuracy and recall.

4.3. **Discussion.** In other research smart lighting is proven in fields of connectivity, energy consumption, and network protocol performances [21-23]. Meanwhile, this study aims for effectiveness. The effectiveness shown by the accuracy value is 87.6%. HHMM is used because it is proven in other fields to provide hierarchical prediction [24-26]. In this study, the nature of HHMM is used to predict activity from movement and lighting mode from activity. Through the mentioned method, HHMM is proven to have higher performance than other machine learning methods, namely HMM, KNN, and Naïve Bayes. The focus of this study complements other studies in the field of AR that have focused on other control, subjects, and methods [27-31].

Note: WI = Work Initiation, RC = Room Checking, RP = Reporting, IDP = IT Data Backup, RS = Resting

FIGURE 6. (color online) Activity to activity probability matrix



Note: WI = Work Initiation, RC = Room Checking, RP = Reporting, IDP = IT Data Backup, RS = Resting, R1 = Lighting Low Mode, R2 = Lighting Medium Mode, R3 = Lighting High Mode

FIGURE 7. (color online) Activity to room probability matrix

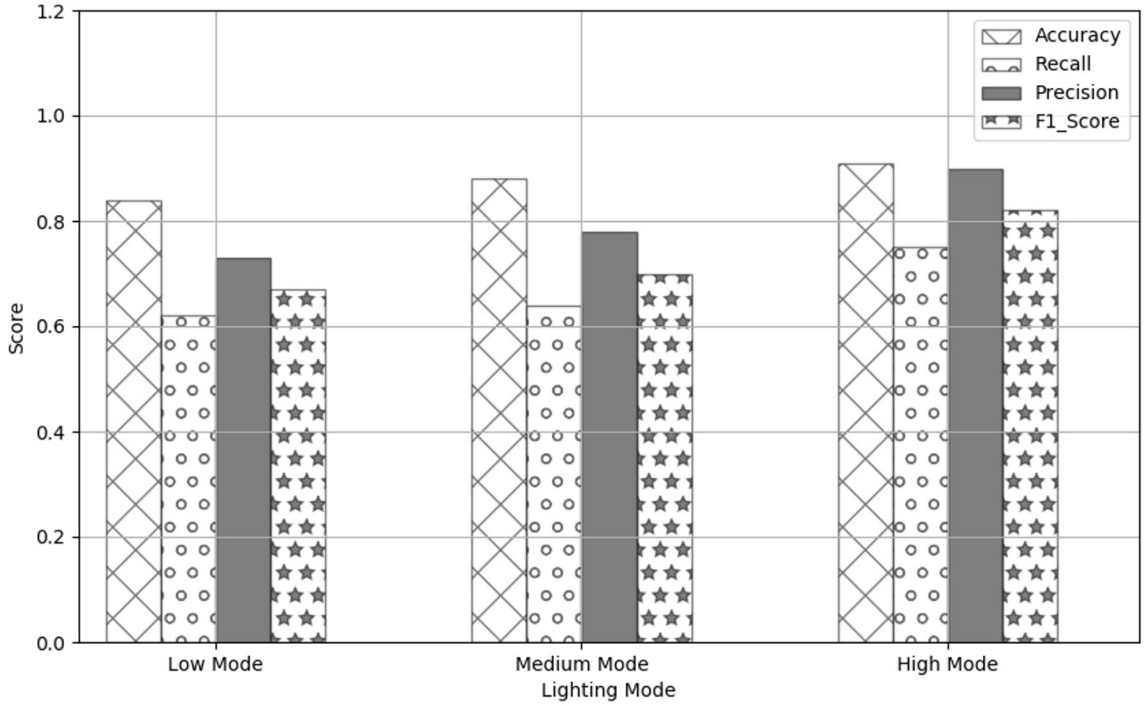


FIGURE 8. Performance of each lighting mode

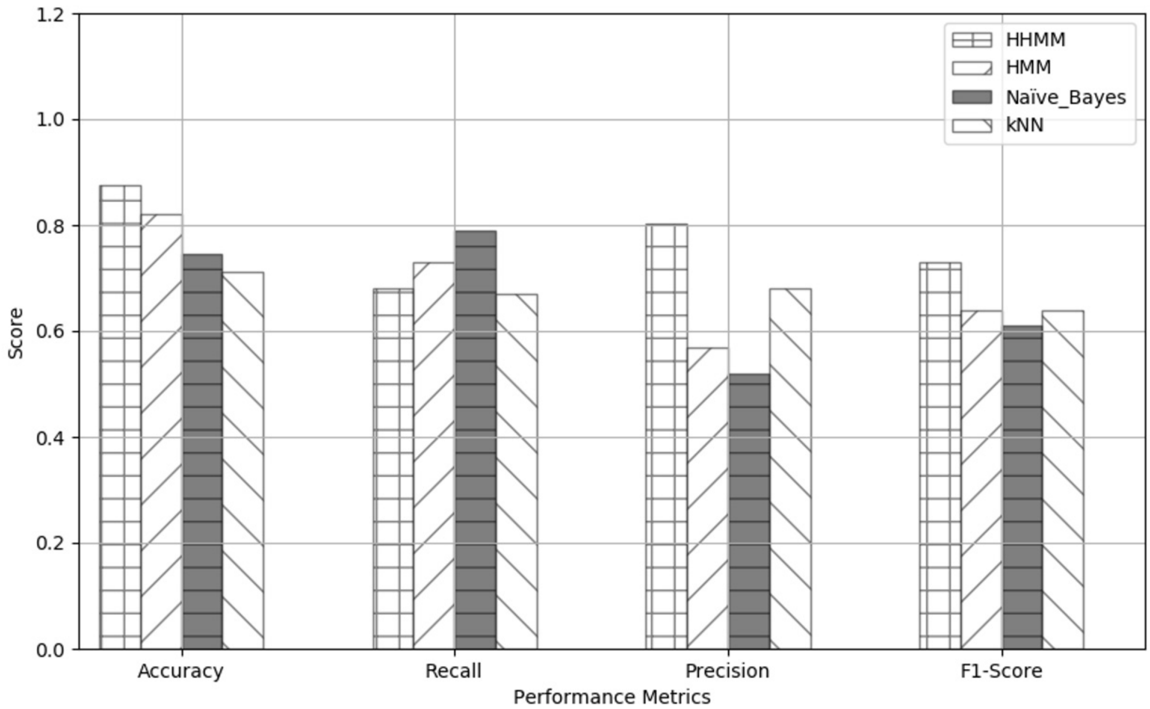


FIGURE 9. Comparison of the performance of each machine learning method

5. **Conclusion.** A smart lighting in office buildings with automatic control utilizing AR and the HHMM learning method has been successfully implemented. In terms of effectivity, this method is proven to be superior to other methods such as KNN, HMM and Naïve Bayes, which has an accuracy of 87.6% in predicting the correct lighting mode based on movement sensing.

Acknowledgement. Authors would like to thank The Ministry of Treasury of Indonesia's Research Scheme (RISPRO LPDP) for funding this research, also for the cooperation of Indonesian Telecommunication Industry (PT INTI) as their industry partner and PT Biofarma as their early adapter partner. Authors also thankfully acknowledge the resource support by School of Computing, Telkom University and all the other research team members that contributed to the research.

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