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Machine Learning Methods in Smart Lighting Toward Achieving User Comfort: A Survey

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ABSTRACT Smart lighting has become a universal smart product solution, with global revenues of up to US$5.9 billion by 2021. Six main factors drive the technology: light-emitting diode (LED) lighting, sensors, control, analytics, and intelligence. The Internet of things (IoT) concept with the end device, platform, and application layer plays an essential role in optimizing the advantages of LED lighting in the emergence of smart lighting. The ultimate aim of smart lighting research is to introduce low energy efficiency and high user comfort, where the latter is still in the infancy stage. This paper presents a systematic literature review (SLR) from a bird's eye view covering full-length research topics on smart lighting, including issues, implementation targets, technological solutions, and prospects. In addition to that, this paper also provides a detailed and extensive overview of emerging machine learning techniques as a key solution to overcome complex problems in smart lighting. A comprehensive review of improving user comfort is also presented, such as the methodology and taxonomy of activity recognition as a promising solution and user comfort metrics, including light utilization ratio, unmet comfort ratio, light to comfort ratio, power reduction rate, flickering perception, Kruithof's comfort curve, correlated color temperature, and relative mean square error. Finally, we discuss in-depth open issues and future challenges in increasing user comfort in smart lighting using activity recognition.

INDEX TERMS Smart lighting, systematic literature review (SLR), machine learning, user comfort, activity recognition.

I. INTRODUCTION

Smart lighting is an innovation whose products are already on the market. A smart lighting product can be a Wi-Fi bulb connected to the Internet. This bulb connects to a downloadable application on a smartphone and a smart home hub such as Google Nest or Amazon Alexa. Turning the lights on or off can be done from the app or based on voice commands via Google Nest. Other commands and features provided by the product are dimming the lamp and changing the lamp's color. The application has features such as setting schedules to when the lights should turn on or off.

The main direction of smart lighting research is energy saving. The cause is the large proportion of energy consumption coming from lighting systems. In some cases, lighting in buildings can contribute up to 40% of energy consumption. Several strategic options allow energy savings in smart lighting, where an example strategy is to apply light sensors to the lighting system. It gives the ability to dim automatically when natural light is sufficient for lighting needs, providing efficiency compared to baseline consumption of up to 25%.

Moreover, user complaints can occur when energy efficiency strategies run on targeted systems due to poor lighting quality [1]. It is understandable because in the rule of energy saving, the more often the lights dim, the better. This phenomenon contradicts the human need for adequate lighting. Some offices maintain a minimum light intensity standard (usually in lux units) to ensure employees' productivity [2]. It even becomes a finding in audit when a violation of lux standard occurs. Hence, the need for user comfort

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and energy efficiency simultaneously becomes a complex matter.

Machine learning is a method that deals with complex problems and automatically generates a solution in the form of a model. Several smart lighting systems have applied machine learning techniques. For example, Advanced smart lighting control uses the convolutional neural network (CNN) for computer vision. K-means, a clustering method, is frequently used to detect lighting levels that users find helpful. Density-based spatial clustering of applications with noise (DBSCAN) method, an unsupervised learning method, can be used to find anomalies in lighting systems. Smart lighting systems that practice recognition, predictive control, and intelligent control use several supervised learning methods. Then reinforcement learning methods are adaptive and can be used for optimization problems.

Furthermore, after considering the mentioned examples, it is possible that machine learning can be a solution to the complex problem of maintaining user comfort and energy efficiency. To our knowledge, no survey paper has thoroughly discussed all the machine learning techniques used in smart lighting research to achieve user comfort. A novel comprehensive survey paper can find the right solution from the available machine learning options to increase user comfort. Suppose user comfort options have existed in previous research. In that case, a research gap can become a future research opportunity to implement smart lighting that applies machine learning to achieve user comfort with a significant contribution.

A. MARKET TRENDS OF SMART LIGHTING

This section discusses the current state of the smart lighting market. We intend to increase awareness and understanding of the actual condition of smart lighting currently on the market. Smart lighting is by no means wishful thinking. The products are on the shelves, ready to purchase, and have developed since a few years ago. Brands are diverse, while customers can find them in shopping search machines via e-commerce applications.

Based on Gartner's statement in 2015, smart lighting could bring savings of up to 90% [3]. There are six main driving factors in smart lighting: 1. light-emitting diode (LED) lighting, 2. sensors, 3. controls, 4. connectivity, 5. analytics, 6. intelligence. In 2016, in the Gartner Hype Cycle for IoT, smart lighting has been running for two years and is in the Trough of Disillusionment position. In 2020, Gartner released six trends in the Hype Cycle for the Digital Workplace. One of them is to "bring your own things" (BYOT). The BYOT trend will shift towards IoT because IoT products will be more personal, including smart lighting. The others are smart bands, voice assistants, virtual reality (VR) devices, and smart earbuds.

According to the Smart Home and Lighting Report 2021 issued by Statista, the scope of the report includes smart lighting products that have sensors and actuators and have computer network connectivity [4]. According to predictions, the Global Revenue of smart lighting in 2025 will be US$ 15.4 billion. This figure will more than double in 2021, which is US$5.9 billion. The United States (US) has the highest revenue forecast, but China has the highest forecast of compound annual growth rate (CAGR) globally. The products that dominate the smart lighting market are Philips Hue, TP-Link, Lifi Labs, and IKEA Tradfi.

From the same report from Statista, smart lighting is a market entry for customers who want to try IoT products, especially smart home products; the reason is that smart lighting is cheap and easy to install. Customers will buy this product first before trying to buy other similar products. Figure 1 shows that the penetration rate forecast of smart lighting is higher than other smart products. In terms of penetration rate, Australia has the highest penetration rate for smart lighting globally, with a value of 13%.

B. RELATED SURVEY PAPERS

Many survey papers have discussed smart lighting, but none have prioritized the comprehensive discussion of artificial intelligence and machine learning methods applied in smart lighting also the applications of each machine learning method. Table 1 shows the survey paper's comparison.

- Füchtenhans *et al.* [5] focuses on smart lighting as a promising technology in the order picking process in the warehouse. Then this paper maps each smart lighting theme to its relevance in the order picking stages. Finally, this paper relates smart lighting to managerial issues.
- Chew *et al.* [6] discusses smart lighting products that are already on the market. This paper also examines the field of communication and visible light communication (VLC) in smart lighting. Finally, this paper concludes that the direction of smart lighting is a combination of several methods to increase efficiency in smart lighting.
- Mora *et al.* [7] discusses the use of multimedia data generated from cameras installed in the city for smart cities. This paper compares image-based smart lighting with other smart lighting concepts such as motion sensor-based and Wi-Fi connections-based smart lighting. Finally, the report evaluates how well each architecture layer processes data in implementing the proposed scheme.
- Wagiman *et al.* [8] discusses smart lighting papers in general. First, this paper categorizes existing smart lighting studies. Then an analysis is carried out on what techniques dominate in smart lighting compared to other methods. The survey results stated that future research should improve the optimization technique for visual comfort.
- In 2019, there has been a study of machine learning methods but more generally on smart buildings, not in the field of smart lighting. Qolomany *et al.* [9] discusses machine learning and also big data in the smart building because it considers there is a vast amount of data in the

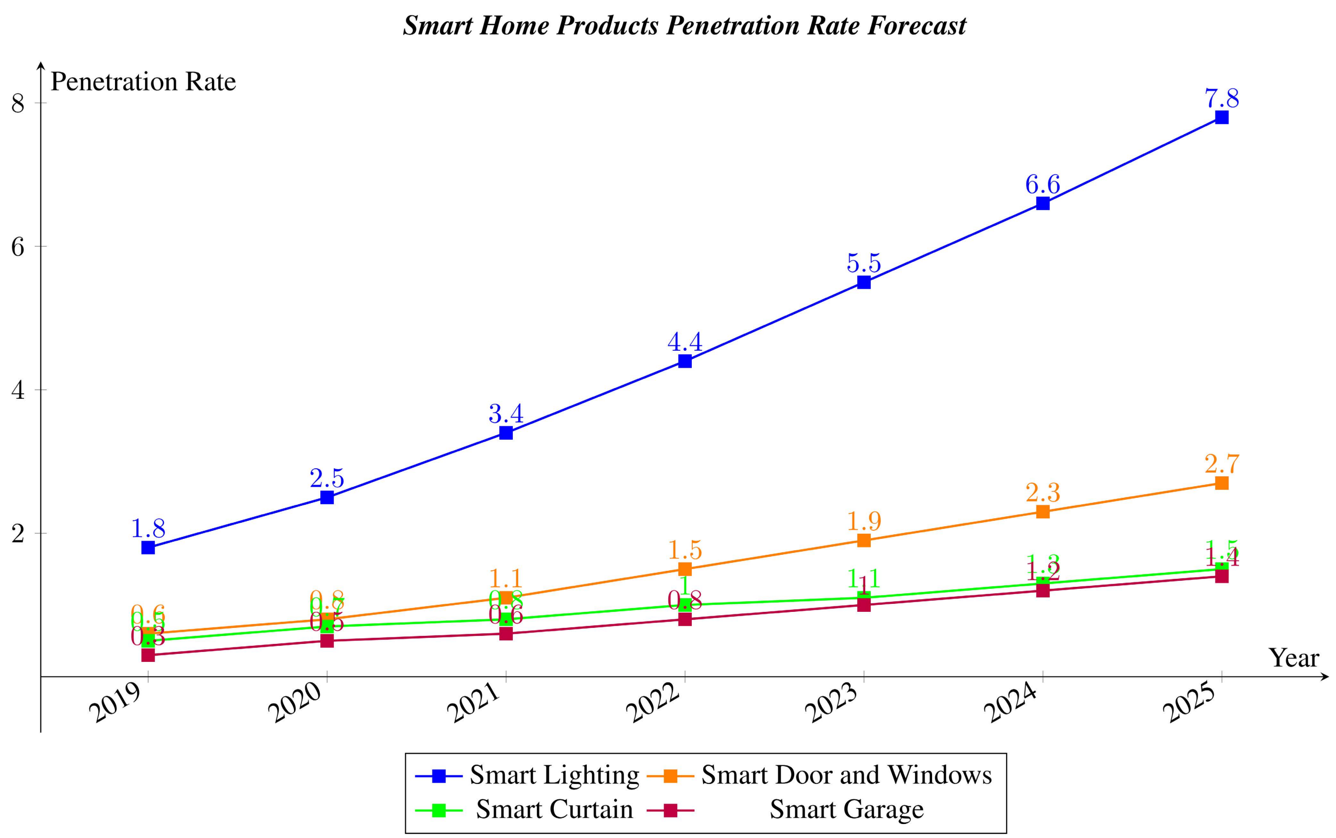

FIGURE 1. A line chart comparison that shows the growth and projection of four smart home products from 2019 to 2025 and displays that the smart lighting penetration rate is higher than other products.

system and data mining is a promising solution. This survey paper discusses products in smart buildings already on the market. This paper also discusses machine learning methods, categorization of these methods, advantages, disadvantages, and their potential application in a smart building.

- Cui *et al.* [10] discusses machine learning, but in the field of IoT, not in the field of smart lighting. Some of the specific things discussed were the application of machine learning in IoT security, edge computing, software-defined network (SDN), and the deployment of machine learning-based IoT.

C. CONTRIBUTION AND ORGANIZATION

To the authors' knowledge, this is the first paper that thoroughly discusses all the machine learning techniques used in smart lighting research. The main contributions of this paper are:

- The mapping of all machine learning methods in smart lighting research since 2014.
- The grouping of machine learning applications in smart lighting.
- The discussion of machine learning topics in smart lighting to increase user comfort.
- The identification of research gaps in the application of machine learning in smart lighting related to increasing user comfort.

The following arrangement of the paper is as follows: Chapter II explains the systematic literature review (SLR) methodology. Chapter III covers smart lighting topics in related research, starting from initial research to the latest research. Then Chapter IV discusses machine learning methods in smart lighting research and the applications of machine learning methods in smart lighting. Chapter V addresses topics about increasing user comfort in smart lighting. Chapter VI conveys research gaps and opportunities in increasing user comfort in smart lighting using machine learning. Chapter VII is the conclusion.

For the reader's convenience, we create a table containing a long list of important terms related to smart lighting and machine learning in Table 2.

II. SYSTEMATIC LITERATURE REVIEW METHODOLOGY

This chapter explains the methodology for conducting the paper survey. This paper uses a systematic literature review (SLR) methodology, which goes through several stages [11], [12]. The stages are: determining the research question, conducting search strategy and selection, then performing data extraction and synthesis.

TABLE 1. Related paper survey comparisons.

Survey Paper	Discussion and Strength	Limitation
Fuchtenhans *et al.* [5]	Focuses on smart lighting research to be implemented in the order picking process in the warehouse. This paper maps each smart lighting theme to its relevance in the order picking stages. Finally, this paper relates smart lighting to managerial issues.	Although there was a comprehensive discussion on issues in smart lighting, smart lighting implementation targets, and the technology used, they were very focused on the warehouse sector. They did not discuss the potential of machine learning methods in smart lighting.
Chew *et al.* [6]	Discusses smart lighting products that are already on the market. They also provide an in-depth discussion on communication and VLC in smart lighting. Finally, this paper concludes that the direction of smart lighting is a combination of several methods to increase efficiency in smart lighting.	While concluding that the future of smart lighting is intelligence and combining several methods for performance improvement, no discussion has focused on machine learning techniques in smart lighting.
Mora *et al.* [7]	They discuss multimedia data generated from cameras installed in the city for smart cities. This paper also compares image-based smart lighting with other things such as motion sensor-based smart lighting and Wi-Fi connection-based smart lighting. Finally, evaluate how well each architecture layer processes data if implementing the proposed scheme.	Focuses more on smart lighting control techniques based on computer vision and data that must be processed using this method.
Wagiman *et al.* [8]	They discuss smart lighting papers in general. First, this paper categorizes existing smart lighting studies. Then an analysis is carried out on what techniques dominate in smart lighting compared to other methods. The survey results stated that future research should improve the optimization technique for visual comfort.	Although concluding that future research should consider visual comfort as the main issue in smart lighting in the future, this paper does not discuss machine learning techniques and research gaps in this field.
Qolomany *et al.* [9]	Discusses machine learning and big data in smart buildings with the motivation that there is a vast amount of data in the system and mining is great potential. This survey paper discusses smart building products that are already on the market. This paper also discusses machine learning methods, the procedures' categorization, the advantages and disadvantages, and their potential application in a smart building.	Although it discusses machine learning comprehensively, namely its types, methods, and existing papers, the focus is on smart building, not smart lighting.
Cui *et al.* [10]	They discuss machine learning in the IoT field. Some of the specific things discussed were the application of machine learning in IoT for security, edge computing, software-defined network (SDN), and the deployment of machine learning-based IoT.	Although it discusses machine learning, it focuses explicitly on IoT, not smart lighting. Then considering the discussion is about IoT and machine learning, which are two extensive topics, the paper is not comprehensive enough.

A. RESEARCH QUESTION

The first step in conducting SLR is to form research questions (RQ). RQ is the essential part of the introduction and motivates in doing SLR [13]. There are three RQs formed to start the search, which includes the following:

- RQ1: What are the topics discussed in smart lighting papers?
- RQ2: What smart lighting papers have applied machine learning?
- RQ3: What smart lighting papers implement machine learning to improve user comfort?

B. SEARCH STRATEGY AND SELECTION

There are two criteria in paper selection: inclusion criteria and exclusion criteria. Inclusion criteria set boundaries in research and help future researchers determine gaps for further SLRs [14]. Inclusion criteria follow the following points:

- String: The string "smart lighting," "machine learning," "user comfort," and "activity recognition" are in the title.
- Language: English, Indonesian.
- Year: 1993 until 2021.
- Publication type: Journal, thesis, dissertation, and conference.
- Accessibility: Documents available in Google Scholar.
- Document type: PDF, HTML.

All topics searched for and not related to RQ should be excluded [15]. The exclusion criteria are inaccessible papers, all downloaded documents whose publication type does not match the inclusion criteria, all papers with incomplete content, and all papers whose content does not match the theme of the research question.

C. DATA EXTRACTION AND SYNTHESIS

After collecting papers through inclusion and exclusion criteria, the next step is to perform data extraction. Data extraction has two stages: collecting paper information based on a data extraction form and the second is to dig deeper through quality assessment (QA). In data extraction, the author will usually fill out a form to collect data that has been extracted

TABLE 2. Abbreviations for smart lighting and machine learning.

Abbreviation	Explanation
6LoWPAN	IPv6 overlow-power Wireless Personal Area Networks
AI	Artificial Intelligence
AdaBoost	Adaptive Boosting
ADC	Analog-to-Digital Converter
ANN	Artificial Neural Network
BMS	Building Management System
CCT	Correlated Color Temperature
CNN	Convolutional Neural Network
DALI	Digital Addressable Lighting Interface
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DNN	Deep Neural Network
DQN	Deep Q-Learning
FPGA	Field-Programmable Gate Array
GA	Genetic Algorithm
GPIO	General-Purpose Input/Output
GWh	Giga Watt hour
I2C	Inter-Integrated Circuit
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
ITU-T	International Telecommunication Union Telecommunication Standardization Sector
KNN	K-Nearest Neighbor
KWh	Kilo Watt hour
LAN	Local Area Network
LED	Light Emitting Diode
Li-Fi	Light Fidelity
LoRA	Long Range Communication Protocol
LPWAN	Low Powered Wide Area Network
LSTM	Long Short-Term Memory
MEMS	Micro Electro-Mechanical System
MPC	Model Predictive Control
MQTT	Message Queue Telemetry Transport
NZEB	Net Zero Energy Building
PCA	Principal Component Analysis
PIR	Passive Infrared
PSO	Particle Swarm Optimization
PWM	Pulse Width Modulation
QoS	Quality of Service
RNN	Recurrent Neural Network
SDG	Sustainable Development Goals
SDN	Software Defined Network
SVM	Support Vector Machine
SVR	Support Vector Regression
TF-IDF	Term Frequency - Inverse Document Frequency
TLS	Transport Layer Security
VLC	Visual Light Communication
Wi-Fi	Wireless Fidelity
WiMAX	Worldwide interoperability on Microwave Access
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Network

from a paper [16]. Table 3 shows the elements in each data extraction form.

After extracting each paper using the data extraction form, the next step is to do a more in-depth extraction through QA. QA is important because it evaluates the quality of the paper sought [17]. In QA, each paper contains background information, problems, objectives, methodologies, and results, with research gaps or future works. Table 4 shows the points in QA.

TABLE 3. Data extraction form.

Data Item	Description
Title	Title of the article
Year	Published year of the article
Author	Author names of the article
Journal	Journal of the article
Publisher	Publisher of the Journal
Volume	The volume and number of the Journal
Keywords	Keywords in the article (given or searched)

TABLE 4. Quality assessment list.

QA Number	Description
QA1	Is the aim of the study clearly stated?
QA2	Does the aim of the study answer the problem statement?
QA3	Is there any statement related to the general problem?
QA4	How is the methodology described?
QA5	What are the paper's results, findings, and contributions?
QA6	Is the research gap explained in the passage?

D. LITERATURE DEMOGRAPHICS

We conducted a survey on 332 papers regarding smart lighting based on the inclusion and exclusion criteria mentioned in the previous sub-chapter. Figure 2 shows the number of smart lighting papers along with the trend line. There is an increasing trend where 59% of the publication year is within the range of 2019 – 2021. This increase in number shows that smart lighting is increasingly relevant and indicates the developing diversity of topics covered, especially in the increasingly attractive application of machine learning in smart lighting.

We studied further the topic of each paper we collected. The topic classification of smart lighting paper is carried out based on issues, targets for implementing smart lighting, and technology. Issues are what motivate researchers to research smart lighting. The target for implementing smart lighting answers the question, "where will the smart lighting be implemented?". Technology is a solution proposed by smart lighting researchers. Classification based on the three sets is done based on the keywords. Some papers do not have keywords, so the keywords need to be extracted from the title first.

Furthermore, we conduct a simple text mining method to summarize important keywords. The steps in the preprocessing stage include tokenization, case folding, data cleaning, removing stop words, and stemming. Then the term frequency-inverse document frequency (TF-IDF) method is used to see which keywords are the most important among

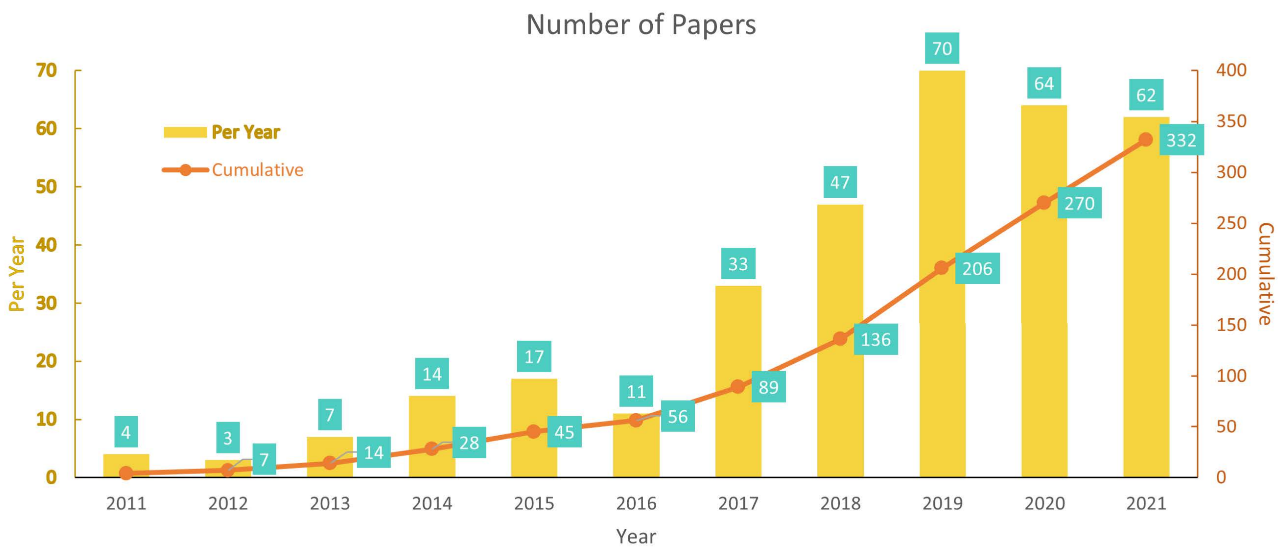

FIGURE 2. A combination chart consisting a bar chart that displays the smart lighting publications growth per year and a line chart that displays the cumulative growth from 2011 to 2021.

the existing keywords. Then we search for the top keywords of each title and sum up each keyword. Finally, we carry out data visualization and reporting.

Based on the keyword search on the issue, there are four main issues when people conduct smart lighting research: energy efficiency, computer network performance, control performance, and user comfort. The four main implementation targets obtained through keyword searches are street lighting, building and office, home, and city. We found six leading technologies through keyword searches in technology: IoT, sensors, LED lights, intelligence, renewable energy, and energy harvesting. By looking at issues, implementation targets, and technology as a set, and looking at each keyword from each set as an element, if a Cartesian product calculates these three sets, there can be 80 combinations of title classes, where several titles can occur within each class.

This review aims to look at the branches of research in smart lighting and assess the state-of-the-art of each field and the technology used. After conducting the analysis, the most exciting topic in smart lighting is energy, with 44 papers, compared to other topics. Interestingly, more smart lighting topics discuss street lighting than other places. The IoT is a dominant topic in smart lighting. It can be understood because smart lighting uses IoT architecture. Six papers discuss comfort in smart lighting. Figure 3 shows the bar chart comparing the number of topics in smart lighting.

III. SMART LIGHTING TOPICS

This section answers the first research question of the survey paper, which explains topics discussed in related smart lighting research. An exhaustive explanation starts with some initial research, goes through general topics, and ends with broad and recent topics related to smart lighting. General topics are then divided further into three categories, including the problem of the research, the implementation target, and the provided solution to each problem.

A. HISTORY AND DEFINITIONS

1993 was the first time there was research on smart lighting [18]. The paper did not explicitly define smart lighting. Still, the paper proposes smart lighting as a system connected to a microcontroller where the microcontroller helps make the lamp functional more optimal. Then, 2003 is the following time an article discusses smart lighting is [19]. The study used MEMS in the lighting system. The paper defines the smart lighting problem as to how to use smart lighting to facilitate building management and whether smart lighting sensor data can be processed into analytics and used for more efficient lighting. Even so, the solutions offered did not yet connect to the Internet. Another critical research in the field of smart lighting was in 2010 [20]. The concept provided by the paper is a clear separation between sensors, control units, and actuators. The paper defines that the target of smart lighting is lighting that is adaptive based on context and preferences. However, the solution does not involve an Internet connection.

Only in 2011 did the same author propose separation between the sensor-actuator (referred to as the end device) and the controller connected to the Internet connection [21]. The paper is arguably the Internet's first implementation of smart lighting. The paper defines *smart lighting* as a system with sensors and actuators connected in a network that works together to achieve user needs. The first implementation of IoT in smart lighting was a paper in 2014 [22]. In the proposal, a smart lighting system applies the complete architectural layers in the IoT, including the application layer. Users can

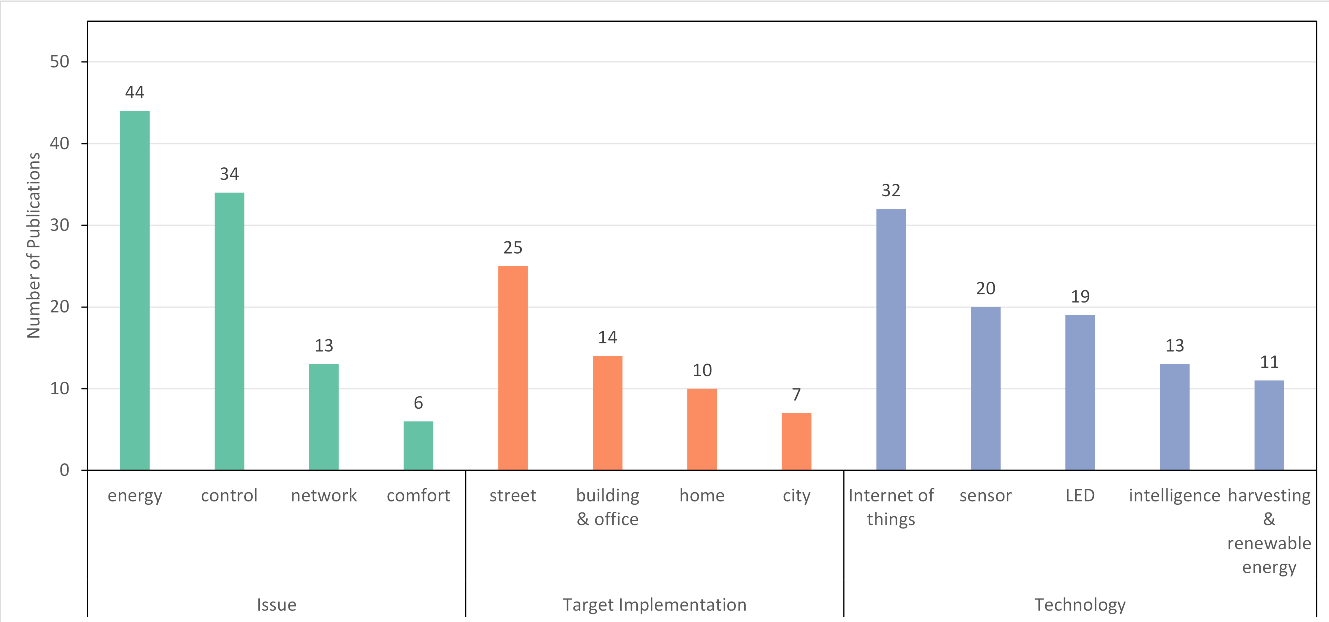

FIGURE 3. A bar chart that shows the number of publications on three main topics of smart lighting where each topic is divided into subtopics of interest.

directly monitor and control the system through a dashboard. Similar to the previous paper, this paper defines *smart lighting* as having sensors and actuators to control the lighting system. In the same year, Guo *et al.* [23] applies machine learning to smart lighting, namely AdaBoost learning on sensor data for intelligent control. However, the solution did implement IoT, which means that there is no IoT-machine learning convergence yet.

In 2020, Soheilian *et al.* [24] defines *smart lighting* as a system consisting of LED lighting, internet connectivity, and optionally sensors to achieve optimal lighting with a control system. Chew *et al.* [6] add to the definition that in the future smart lighting will combine intelligent algorithms with IoT. Then according to Gartner, five essential components in smart lighting are LED lighting, sensors and actuators, connectivity, analytics, and intelligence. So it can be said that smart lighting is a lighting system with a control system, sensors, and actuators connected to the Internet and can rely on artificial intelligence and data science. Then it can be added in the definition that smart lighting aims to optimize lighting for user needs and get energy savings.

B. SMART LIGHTING ISSUES

1) ENERGY EFFICIENCY

Energy efficiency is not a recent issue. Based on a statement in a study by Kolomiets [25], the issue of energy efficiency first emerged in the 1970s, when the oil economic crisis began to emerge. At that time, Western countries started to incorporate energy efficiency into government programs for the first time. Outdated and inefficient systems can also play a role in wasting energy [26]. With the proposed government program, the savings achieved are 2 to 2.5 times. Europe carried out programs to replace fossil-based energy sources with alternative energy sources. Soheilian *et al.* [27] stated that from 1993 to 2009, there was an increase in electricity consumption in housing by 32%. The problem stems from lamps with a low lifespan compared to office buildings and inefficient electricity use. The nature of home energy utilization is the low energy investment cost. Ironically, This can result in increased operational costs.

The proportion of lighting waste to the total electricity consumption waste can vary according to the area and its use. According to Martirano [28], in Europe, lighting can contribute up to 40% of energy consumption in medium and large buildings. A political campaign responded to this in the EU regarding energy saving. This figure can change based on the case, as in Indonesia, the portion of lamps in its energy consumption is 30%.

The problem of electricity waste is also dynamic, considering that the electricity waste faced today is different from the pain of electricity waste 30 years ago. According to Castillo *et al.*, [29] in addition to saving, the trend of waste and energy demand due to smart lighting is also increasing. Due to the rapidly growing urban life, it will reach 2/3 of the population in 2050. The growth will cause the need for lighting in public areas, increasing electricity consumption and light pollution. The increase in the greenhouse effect puts pressure on the private and public sectors to find more sustainable solutions. According to Brown *et al.* [30], in California in 2020, there is a bill that requires that energy savings must be doubled by 2030. The solution is to reduce energy consumption while increasing the performance of the building management system and its supporting infrastructure. Technology is key in achieving this target. Outdated technology becomes a gap that makes it challenging to achieve this goal. The current system does not have the communication and intelligence capabilities to collect and process the required information, such as the status and usage of lights. Castro *et al.* [31] say that energy efficiency is the first goal in achieving sustainability. Sustainability itself is a target to be gained from a smart city, especially in industry, buildings, and residents [32]. The impact of achieving 40% energy efficiency in lighting is reducing half of the energy waste that the world produces.

Many countries have taken serious actions against the greenhouse effect and global warming. González-Amarillo *et al.* [33] state that a building's energy consumption can reach almost zero. Implementing the European Energy Performance of Buildings Directive (EPBD) to achieve this target is necessary. EPBD is the main instrument of the EU legislature to improve energy performance in buildings over its community. The Kyoto Protocol inspired the policy, which made EU members commit to reducing energy emissions in buildings with binding targets. The Kyoto Protocol is an international treaty approved by 192 parties regarding commitments to reduce greenhouse gas emissions.

2) SMART LIGHTING CONTROL

The basic of smart lighting is automatic light control. The complexity of a problem in smart lighting affects the proposed control solution. According to Hsia *et al.* [34] there are two types of control in smart lighting, namely manual control and automatic control. Automatic control can apply simple control using a passive infrared (PIR) sensor to detect motion. Meanwhile, complex controls such as multi-color lighting control need intelligent methods such as artificial neural networks (ANN). The ANN method was also in use in a complex problem of the research by Seyedolhosseini *et al.* [35]. The ANN method controls luminaire dimming with system faults and daylight variation detection without increasing complexity. Apart from ANN, Karyono *et al.* [36] also mentions other methods to improve control of smart lighting, for example, using reinforcement learning methods to increase knowledge of schedule-based control as well as occupancy-based control. The complex control based on schedule information can control room lighting based on various conditions such as lighting and blinds simultaneously with satisfying performance.

Several control techniques have been introduced in smart lighting, for example, detecting a linear relationship between the light sensor and the dimming level. A more complex system appears when the workplace is large with several controlled lights, then the position of the light sensor is also a consideration [37]. Adams *et al.* [38] reveals that lighting control capabilities need to be more sophisticated to achieve the net-zero energy building (NZEB) target. A more sophisticated control can use camera-based or digital sensing. The microcontroller also makes control easier because it implements digital solutions. Aspects that are advanced include design time, dimension, and price. Gagliardi *et al.* [39] say that lighting control is essential in reducing energy consumption. Even though a smart lighting system applies IoT, it must focus locally on lighting control. Control strategies should focus on light intensity based on related context. For example, smart lighting control for streetlights should consider traffic conditions.

3) SMART LIGHTING NETWORK

Several choices and options are applicable for a smart lighting network. For example, choosing between wired or wireless communication in a system brings consequences. According to Krasniqi and Vershevci [40], choosing the proper communication protocol for smart lighting is difficult because each protocol has its advantages and disadvantages. Besides, smart lighting in the market is available with predefined communication protocols. In an example case, the Z-Wave Protocol is a low-power protocol but is not IP-based, so networks that use this protocol may not necessarily be able to connect to the Internet. Even so, this protocol makes it easy to control smart home devices. Prittinen *et al.* [41] explains that recent technologies are still bound to current communication protocols for smart lightings, such as the Digital Addressable Lighting Interface (DALI) and KNX, which are standards for building automation. The limitations are the wired nature of the protocols, the limited network size, and the redundant infrastructure. These weaknesses restrict the protocols' adaptability in handling the needs of an advanced smart lighting system.

The use of the DALI protocol can enhance communication networks on smart lighting. Bellido-Outeiriño *et al.* [42] proposed a lighting network system with the combination of IEEE 802.15.4 wireless standard and DALI protocol. The benefits of the proposed system are installation efficiency provided by the wireless protocol and an effective bidirectional control served by the DALI protocol. Ordaz-García *et al.* [43] proposed shifting the DALI protocol on microcontrollers from software to hardware using a field-programmable gate array (FPGA). This shift results in a low-latency, power-efficient solution.

Communication range is also an issue in smart lighting networks. Sutil and Cano-Ortega [44] created a bibliographical review on the available wireless technologies for smart lighting. Results show that some smart lighting technologies still do not depend on wireless technology. Other research uses wireless technologies such as Wi-Fi, GSM, low-powered wide-area network (LPWAN), Zigbee, and WiMAX. LPWAN is a generic term encompassing all protocols that focus on long-range, low-powered, and low-bitrate communications. The long-range (LoRa) network is an example protocol considered as LPWAN. The development of LoRa is interesting because of the openness of its higher-level protocol, LoRaWAN. LoRA also provides a range of low price devices. Zigbee is a wireless personal area network (WPAN) communication group that is power-efficient and cost-effective. Leccese [45] proposed Zigbee as a communication protocol in a street lighting system with remote control capabilities. Zigbee can resend packet verifications with a reliability level of 99.87% to 100% in various scenarios.

Some new paradigms emerge in cloud computing solutions on smart lighting networks. According to Mijuskovic *et al.* [46], cloud computing for smart lighting has advantages. Still, when dealing with large data sizes, cloud computing has limitations, such as location and delay. The concept of fog computing is applicable to overcome the limitations of cloud computing.

Light is a form of wave and, like radio frequency (RF) waves, can be used as a communication medium. Ajithkumar *et al.* [47] explains that visual light communication (VLC) still works like the very first form of wireless communication using fire and smoke signals. As human history advanced, the method developed into a signal lamp, using visual signaling for optical communication. VLC works just like signal lamps but with an ultra-higher speed, where its bitrate can make up to 800 THz. Vu *et al.* [48] mention that visible light has the potential to be used as communication in smart lighting. The concept is that LED lights and dimming control act as the message sender. A light sensor acts as the recipient of the message. The Institute of Electrical and Electronics Engineers (IEEE) 802.15.7 and its amendments are standards for VLC. One of the most critical requirements for VLC is to exhibit no flickering to the human eye.

Like VLC, smart lighting power line communication (PLC) is significant, especially for street lights. Kiedrowski [49] explained that since its introduction as the International Telecommunication Union Telecommunication Standardization Sector (ITU-T), PLC has succeeded in increasing the bitrate in smart lighting communications. Nevertheless, the drawback of PLC is its reliability. Several cyber security issues also need to be faced by PLC, with smart grid vulnerabilities as a risk. The spread spectrum nature of PLC makes PLC suitable for using the orthogonal frequency division multiplex (OFDM) transmission technique. Digital modulation methods such as binary phase-shift keying (BPSK) and quadrature phase-shift keying (QPSK) can be used over OFDM on PLC [50].

4) USER COMFORT

Several cases can illustrate the importance of user comfort in smart lighting. In a study made by Cheng *et al.* [51], smart lighting works in subway trains where the number of passengers is small. Turning on all the lights with a dimming level of 100% would be a waste. Nevertheless, on the other hand, if the lights become dim, passengers will feel insecure and uncomfortable. Thus, user comfort will be disturbed. Park *et al.* [52] also stated that in railway lighting, user comfort is one of the essential aspects besides security, promptness, and convenience. The proportion of lighting in the railway system energy consumption is very high. Given the importance of the two issues, producing technology to increase train lighting energy efficiency should not sacrifice user comfort.

Some researchers say that user comfort comes from technological sophistication. For the home environment, according to Soheilian *et al.* [53], smart lighting is part of a smart home that provides comfort, convenience, and security and satisfies residents' needs. The two most common goals for smart lighting are energy savings and visual comfort. However, current research still focuses on the technical achievement of a proposed system without properly addressing well-being and comfort issues. User comfort becomes a research opportunity in the field of smart residential lighting. Kumar *et al.* [54] explain that visual comfort can increase by using an Android App. Android comes with a powerful interface that allows a person to adjust the lights, either automatically or manually. The ideal smart lighting control must adapt according to the conditions of the occupants and environmental conditions.

User comfort, in several ways, is related to efficiency. Wang *et al.* [55] says that by adjusting the lighting level based on existing natural light, the intensity of light in an environment can be kept constant. The adjustment can increase savings and convenience. Maharani *et al.* [56] said that there is a contradiction when the lights turn off. On the one hand, it saves energy, but on the other hand, the light intensity decreases. So that the smart lighting function increases, not only looking for lamp savings but also looking for a balance between minimum energy and maximum lighting.

Another aspect of user comfort apart from visual needs and technological sophistication is sleep comfort. Takemura *et al.* [57] say that poor sleep quality can be affected by lighting that is too bright. On the other hand, too low lighting can also reduce the quality of life (QOL), so softer lighting should not reduce QOL. On the other hand, but still related, Akbar *et al.* [58] underlines that one of the causes of wasting electricity is the use of lights when people are asleep. If a system exists where the artificial lights can turn off automatically when people fall asleep, then the benefits are two-fold: energy savings and improved sleep quality.

Several parameters can measure user comfort, both subjective and objective. Kwon and Lim [59] uses a parameter called Kruithof's comfort curve to evaluate the performance of its smart lighting. Kruithof's comfort curve can determine the user's comfort area in a plot between light intensity and color temperature. Some today's smart lights only rely on motion sensors limited to human motion, not human presence. It causes the possibility that when someone is under artificial light, the light remains off. To not disturb the user, the lamp should predict the user's activity pattern first and then decide on the status of the light on or off.

C. IMPLEMENTATION TARGET

1) STREET SMART LIGHTING

Like each smart lighting installation target, street lighting has its unique problems. Mahoor *et al.* [60] said that the problems surrounding street lighting are reliability, resilience, energy costs reduction, and environmental issue management. The unique property of street light is that it is ubiquitous. Omar *et al.* [61] revealed that because street lamps are a necessary facility of a city, the consumption of streetlamps will also affect the economic condition of a country. Adjusting the street light is tricky because if it is too dim, it will affect the safety of road users.

As with general smart lighting problems, energy efficiency is also a problem with street lighting. According to Martinek *et al.* [62], street lighting contributes 15% of national energy consumption. The current street lighting is still very inefficient. For example, the lamp will illuminate with maximum illumination even though no one uses the road. Data from Qaisar *et al.* [63] shows that street lamps worldwide have an energy consumption of 8760 Giga Watt-hour (GWh). That is to assume that there are 100 million street lamps globally. Based on data from Dwiyaniti *et al.* [64], outdoor lighting in the United States (US), which mostly comes from roads and parking lots, consumes 120 hours of energy. The same amount of energy could be used to power the whole of New York for two years. While according to Tomczuk *et al.* [65], in Europe, 1.3% of total energy consumption comes from roads. Then two-thirds of the existing lights do not meet the standard that they should.

There are several causes of wasted electricity in street lights. Gupta and Gupta [66] state that the existing lighting technology does not reflect the progress of other technologies in the world. Waste that occurs and comes from lights can occur for simple reasons such as street light management forgetting to turn off the lights when it is morning. Paschalis *et al.* [67] explains that some of the causes of wasted street lamps include a low lifespan, turning on and off not based on actual conditions, conventional malfunction detection, and soft lighting quality.

Several deployed street lighting solutions have implemented technology, although they are not yet the latest technology. Smys *et al.* [68] revealed that currently available technologies for street lighting are timers, nightfall sensors, and astronomical clocks. These technologies can still be improved to increase the energy efficiency obtained from street lights. Meanwhile, according to Galatanu [69], using the astronomical clock to turn the lights on and off will cause problems. The article states that special events such as clouds or rain do not include in the method's calculation. In addition, Petrioli *et al.* [70] directly compare astronomical clock systems with systems that employ dimming capabilities based on the information on average traffic flow rate. The dimming capability brought by the proposed system allows for energy efficiency.

In addition to the points already mentioned, there are many other considerations in smart lighting for street lights. Among others, Mohit *et al.* [71] argue that street lighting must be more sophisticated because roads are a strategic interest of every state. Roads keep the country's supply chain safe by bringing logistics such as equipment, materials, and essential goods.

2) OFFICE AND BUILDING SMART LIGHTING

Lighting in office buildings provides a proportion of waste that varies between cases. According to Acosta *et al.*, [72], lighting energy consumption in the building is 15% to 30%. Cihan and Güğül [73] adds that energy consumption in commercial buildings in the US is up to 25%, and in Turkey, it is up to 9%. The primary strategy for energy savings in the lighting sector is to utilize daylight.

Besides LED lighting, dimming capability is also important in achieving energy efficiency. In addition, another solution is by reducing the illumination time. Neardy *et al.* [74] say dimming can provide efficiency up to 40% and increase visual comfort.

Smart lighting in the office is unique because the office is a place to work. Hajjaj *et al.* [75] explains that apart from energy consumption, office lighting can also affect work productivity. Intelligent lighting applications in the office can even customize lighting based on individual needs. Li *et al.* [76] said that the suitability of indoor illumination was also a topic. Sakaci *et al.* [77] said that the consumption of electrical energy from office lighting has a correlation with the workload in the office and will increase during peak hours. In addition to this, the lighting system needs monitoring. If the workload exceeds the limit, the electricity will drop, fatal to the network whose performance comes from its uptime.

3) SMART HOME

Smart lighting at home becomes part of a larger smart home system. A smart home is typical building automation for residential. The particularity of a smart home compared to a smart building is that the arrangement is not massive. Andramuño *et al.* [78] argue that home automation combines automation technology, computing, and computer networks. The benefits provided by home automation are in the areas of convenience, security, and energy savings. Ayan and Turkay [79] add in the definition that those who control remotely can be smartphones, laptops, or other items connected via the Internet. Rajarajeswari *et al.* [80] revealed that one of the causes of electricity wastage is the failure of householders to turn off electronic devices when not in use. Automation becomes paramount in the provision of smart homes.

Because the application is at home, several technologies can be added to the smart home, for example, a smart home combined with renewable energy such as solar panels. According to Martin *et al.* [81], in the era of renewable energy, energy consumption strategies at home need to be regulated. For example, it should be heavily consuming when renewable energy increases and sparingly when not made.

4) SMART CITY

In applying smart lighting in smart cities, urbanization is often a source of problems. Yang *et al.* [82] reveal that 50% of the world's population lives in cities. Pasolini *et al.* [83]

state that because a large number of people live in cities, urban development must be sustainable. Because cities account for 75% of the world's energy consumption, one of the factors in sustainability is how to save electricity consumption. Gagliardi *et al.* [84] adds that the increase in energy consumption will focus on big cities, not small cities. 80% of the total energy generated will flow to the smart city grid.

In addition to urbanization, the hallmark of a smart city is the ubiquity of connected devices. The number of smart devices embedded in each human being added to the number of smart devices embedded in the infrastructure causes a considerable amount of data to be used, among others, for smart lighting.

Smart city lighting is not only about energy saving. Still related to sustainability, smart lighting in cities is also associated with urban design. Braw [85] says that smart lighting in cities not only turns on when people need it and turns off when people do not need it but can also change color to adjust the atmosphere to what the residents want. Smart lighting in such a way will be a sustainable and fun solution.

D. SMART LIGHTING TECHNOLOGIES

1) LED LIGHTING

In October 2012, Phillips Hue, a lighting product from Phillips that implemented LED lighting, was first launched. Since LED lighting began to market to replace fluorescent lamps, various conveniences and improvements in lighting quality have emerged. Wu *et al.* [86] said that the optical efficacy of LED lighting had reached 72 lm/W. This figure means that LED lighting is 75% more efficient than mercury lighting, which widely exists for street lamps. Then Hui *et al.* [87] adds that LED lighting has a longer lifespan, which is up to 80,000 hours.

The advancements brought by LED lighting are multidimensional. LED lighting already brings significant efficiency improvements over conventional lighting without intelligence and computing. Askola *et al.* [88] revealed that LED lighting had become an essential driver in the industry in recent years. There is a massive potential for savings when replacing conventional exterior lights with LED lights. In Germany, the savings obtained by replacing lamps with LED lamps is 400 million euros.

Not only efficiency, compared to conventional lamps, LED lighting is easier to control for light intensity and color. According to Kim *et al.* [89], LED lighting is also a driving force in customized interior-lighting design. Compared to conventional lamps, the advantages of LED lighting are that it is efficient, has a longer life, has the freedom to adjust color, and freedom to adjust light intensity. Bagheri-Sanjareh *et al.* [90] say that to control LED dimming, there are several approaches. Ways to control LED dimming include analog dimming and pulse width modulation (PWM) [91] dimming. Abdurohman *et al.* [92] explains that the dimming capability of LED lighting can add to the savings already obtained from manually turning on and off settings.

Measurements need to prove that LED lighting can deliver savings. Strategies in measurement and comparison, benchmarks, and standards need to emerge. Ahmed *et al.* [93] say that there are several ways to measure LEDs. Measurements to calculate the energy consumption of LEDs can occur for one year. The size of light intensity can use simulation with tools. Jha and Kumar [94] said that in LED development, there is a standard, namely EC 61000-3-2 Class C. Meeting these standards involves developing several intelligent solutions.

2) SMART LIGHTING SENSORS AND ACTUATORS

The sensors commonly used in smart lighting are motion sensors, occupancy sensors, and light sensors [95]. The light sensor is for efficiency, while the motion sensor is for user comfort. Ciabattoni *et al.* [96] reveals that in monitoring smart lighting, several sensors need to operate at once. In addition to motion sensors and photosensors, temperature sensors can also become part of the system. Hoang *et al.* [97] add that the performance of smart lighting control depends on the light sensor. Therefore, making a reliable light sensor is very important.

In smart lighting, each sensor has its way of working. Tan *et al.* [98] say that a sophisticated lighting control system involves an occupancy sensor and a light sensor to control the light based on natural light and achieve efficiency. These sensors become feedback in a control system design. Afshari and Mishra [99] reveal that color sensors can also be part of smart lighting. Color sensors are used for decentralized control and optimizing setpoint targets.

One of the smart lighting strategies is to use human presence to control the on/off status of the lights. Chun and Lee [100] in their research said that ultrasonic sensors and PIR sensors estimate human location and function to turn on or turn off lights in smart lighting. It is because people's light needs to change depending on their activities. Tetervenoks *et al.* [101] adds that there are two kinds of motion sensors: active motion sensors and passive motion sensors. Active motion sensors, such as radar, continuously emit waves to detect movement.

In detecting motion, cameras are also sensors that are pretty common in smart lighting besides motion sensors. Movement can be seen from images via cameras with the implementation of computer vision. In addition to the sensors already mentioned, other sensors have also been part of the system, namely the current sensor, temperature sensor, and gas sensor.

The actuator controls the lights. The two primary actuators used in smart lighting are the relay which turns the lights on or off, and the dimmer which dims the lights. Other actuators that are not directly connected to the lighting system but add other functionalities are buzzers, LCD screens, and servo motors.

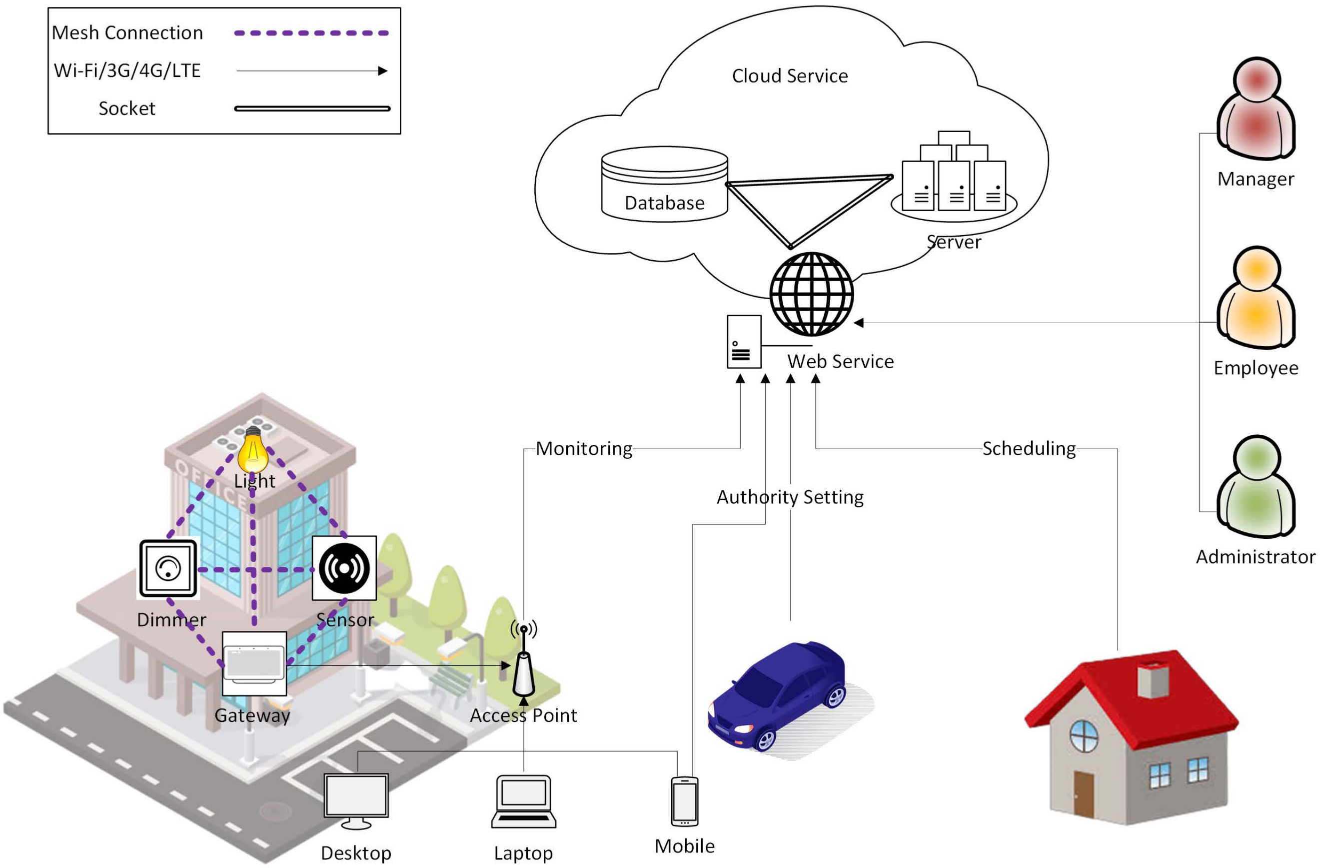

FIGURE 4. An illustration that shows an example of the layout of a complete smart lighting system applicable to a corporation where the solution connects to a cloud computing environment, extensive connectivity, and diverse user role management.

3) INTERNET OF THINGS

Smart lighting and IoT are two different technologies. However, IoT is arguably the main driver of smart lighting. Figure 4 shows an example implementation of smart lighting. A lighting system will communicate with dimmers and sensors via the access point. Then there is the user application, where the example in the picture is a desktop that can show the performance monitoring of the lighting system. Communication between each entity uses Wi-Fi, locally or via Internet [102].

A typical IoT architecture for smart lighting looks like Figure 5. The IoT architecture consists of 3 layers: the end device, platform, and application. The end device layer consists of four main parts, namely sensors, microcontrollers, communication network modules, and actuators [103]. Common sensors in smart lighting are motion sensors and light sensors. Then each architecture is supported by the internet communication protocol as a liaison for each layer.

Several microcontrollers and mini personal computers (PCs) can build the **end device layer** in IoT smart lighting, where examples are BeagleBone, Arduino, Raspberry Pi, and NodeMCU. Arduino is a microcontroller board with the ability to input, output sensors and actuators, both analog and digital [104]. However, Arduino cannot connect to the Internet, either wired or wireless [105]. So to communicate with the Internet to form an IoT platform, Arduino can be combined with NodeMCU [106]. NodeMCU has a Wi-Fi module built into its chip and can expand to Arduino's Integrated Development Environment (IDE) [107]. However, NodeMCU's hardware capabilities are not as good as Arduino's, so its use is usually combined with Arduino and communicates with I2C. The most widely used type of Arduino is the Arduino Uno which uses the ATmega328P chip with the AVR architecture.

The Raspberry Pi (Raspi) can be a member of the mini PC category because it has a high-level input-output and can connect to devices such as a monitor, keyboard, and mouse [108]. However, the Raspberry Pi cannot be a microcontroller because, although it has a general-purpose input/output (GPIO) to connect with digital sensors, it does not have an analog-to-digital converter (ADC) to read analog sensors. Usually, the Raspberry Pi will add modules such as Arduino. The Raspberry Pi processor uses the ARM architecture, suitable for single-board computers because it is cheap,

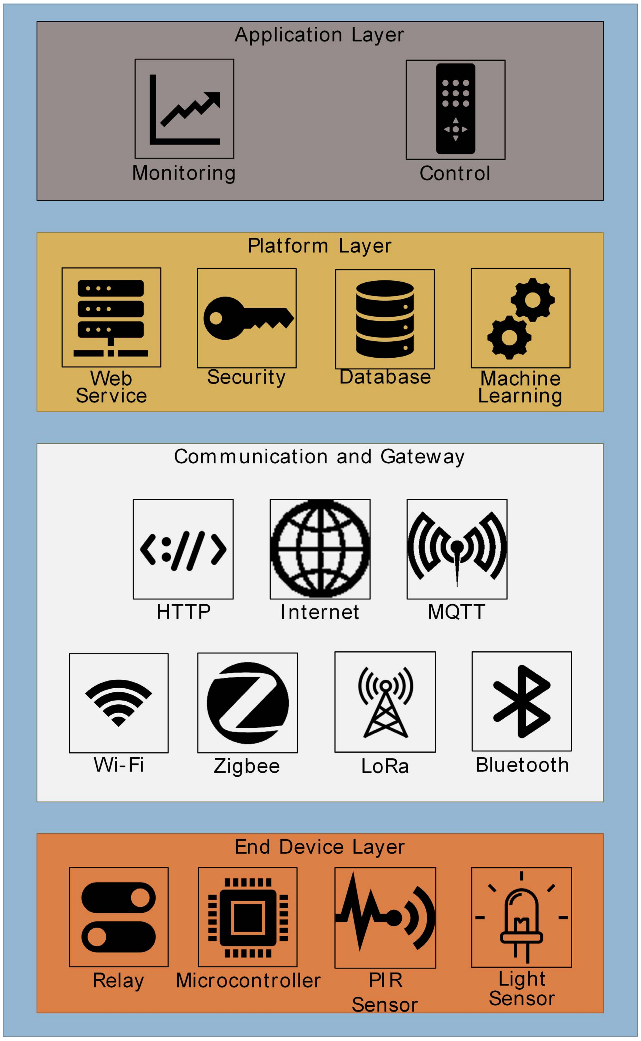

FIGURE 5. A typical IoT architecture for smart lighting with three main layers: end device layer, platform layer, and application layer, supported by communications to connect all layers.

small, but compact. The most popular Raspberry Pi is the Raspi 3B+ with its most known characteristics, among others are 4 USB sockets and a full HDMI socket.

BeagleBone has capabilities like the Raspberry Pi, in terms of its microcontroller has an ARM architecture. In addition, BeagleBone also can communicate via Ethernet. Plus, BeagleBone also has a sound input-output as a microcontroller, but when compared to Arduino, BeagleBone has a relatively higher price. Xbee is a microcontroller with Zigbee communication capabilities, but Xbee usually uses an additional module in Arduino.

IoT involves machine-to-machine communication and human-to-machine communication. The task of the IoT **platform layer** is to make everything connected, including contact from the microcontroller and also the web service for the user [109]. ThingSpeak is a form of an open data platform for IoT [110]. ThingSpeak is a cloud service that can monitor sensor data and provide a web service so that data can be accessed remotely [111]. ThingSpeak also has an interface to communicate with the MQTT Protocol. Another platform is Node-Red, which is an IoT platform based on Node.js. Node-Red has scalability and can be used to connect web services with IoT devices [112]. Besides ThingSpeak and Node-Red, there is also Thinger.io. Thinger.io can be used as a cloud service like ThingSpeak and can also be downloaded and installed to form a private server like Node-red [113].

In the **application layer**, the technical option is to access the system on a mobile or desktop device. Blynk is an open-source smartphone tool that can easily create mobile applications for communication with smart things [114]. With Blynk, programmers can choose features for the user interface such as buttons, sliders, or gauge [115]. Blynk can do monitoring functions and also control functions [116].

In addition to Blynk, programmers can also develop their web or take advantage of web services from the IoT platform, which usually already has a good user interface. Web services can connect to web browsers owned by every device and operating system to be accessed easily. Website development can use JavaScript-based Bootstrap. Socket IO is also another JavaScript-based framework option where its server-side runs on Node.js.

Communication plays an important role in connecting each layer. Zigbee is a wireless communication model that has a short distance and has small bandwidth, making it suitable for implementing IoT [117]. However, Zigbee devices, usually Xbee, have a relatively high price. Bluetooth, like Zigbee, has a short communication range. Compared to Zigbee, Bluetooth has greater bandwidth, so its power consumption is also greater. Bluetooth modules have a relatively low price and can pair with Arduino.

Long Range (LoRA) protocol is communication with a small bandwidth and has a long communication distance [118]. Wi-Fi is a common standard for local communication with large bandwidth. The common Wi-Fi communication module in IoT is the NodeMCU which has a relatively low price. After setting up, the Blynk App can then control and monitor smart things.

Wired communication options are not much vast in smart lighting, being PLC and DALI among them [119]. DALI can function as a transceiver between smart lighting and their external devices. Information that enters and leaves the system includes current sensor data and lamp control data [120]. DALI is an interface that provides interoperability in controlling lights from various products [121].

End device nodes, if used on a large scale, can form a wireless sensor network (WSN) [122]. Topology options in WSN such as grid and tree can optimize WSN network performance [123]. Extensive WSN communications can rely on a multi-hop routing. Thus, a routing protocol that has high compatibility and extensibility is needed, such as IPv6 over low-power Wireless Personal Area Networks (6LoWPAN) [124].

TABLE 5. Recent IoT architecture for smart lighting comparison.

Paper	End Device Layer			Platform Layer		Application Layer		Communication Network & Protocol
	Sensors	Actuator	Micro-controller	Platform	Capabilities	Type	Tools	
Srivatsa *et al.* [125]	Camera		BeagleBone	Server	Database, Web Service	Laptop	Web	Ethernet
Kumar *et al.* [126]	None	Relay	Arduino Uno	None		Mobile	Android Application	Bluetooth
Mahandran *et al.* [127]	None	LED, Servo	Arduino Uno, ESP8266	None		Mobile	Blynk	Wi-Fi
Rudrawar *et al.* [128]	Ultrasonic	Dimmer	Arduino Uno, NodeMCU	Server	Sunset/Sunrise Data, Web Service	Laptop	Computer Application	Wi-Fi
Aparna *et al.* [129]	Camera, Switch	Relay, Display	Raspberry Pi	None		None		None
Leccese *et al.* [130]	Light, Presence	None	Xbee	Raspberry Pi	Web Service	Mobile, Laptop	Web	Zigbee, WiMAX
Fanoon *et al.* [131]	Light, PIR, Energy Meter, Temperature	Dimmer, Relay		Server	Web Service	Mobile, Laptop	Web	Modbus, MQTT, HTTP
Montalbo *et al.* [132]	PIR	Relay	NodeMCU	Server	Database, Web Service	Laptop	Bootstrap	Wi-Fi
Khoa *et al.* [133]	PIR	LED, Buzzer	ESP8266	Socket.io, TinyDB	Security, Database, Web Service, App API	Mobile, Laptop	Socket.io	Wi-Fi
Tang *et al.* [134]	None	Dimmer	Raspberry Pi, Arduino Uno, Xbee	Server	Web Service	Mobile	Android Application	Zigbee, TCP, TLS, HTTPS
Feng *et al.* [135]	PIR	LED	STC89C52 Minimum System	None		Mobile	Android EA4	Bluetooth
Gehlot *et al.* [136]	Camera, light, temperature, humidity, CO, NO	Dimmer, Relay	ESP32	Tensorflow	Web Service, Encryption, Computer Vision	Mobile, Laptop	Web	LoRA, Wi-Fi, Bluetooth, REST, WebSocket
Higuera *et al.* [137]	Light, PIR	Dimmer, DALI	TI MSP430	ThingSpeak	Monitoring, Web Service	Laptop	Matlab	REST
P.K. *et al.* [138]	Light, PIR	LED	NodeMCU	ThingSpeak	Monitoring, Web Service	Laptop	Web	REST
Riyadi *et al.* [139]	Light, Ultrasonic	Relay	ESP32	ThingSpeak	Monitoring, Web Service	Mobile	Android Application	REST
Garg *et al.* [140]	Light, PIR	Dimmer	Arduino, ESP8266	ThingSpeak	Monitoring, Web Service	Mobile	Blynk	Wi-Fi, REST
Haba *et al.* [141]	RGB	DALI	WF32	WF32	Web Service	Laptop	Web	Wi-Fi, HTTP

A comparison of recent IoT architecture for smart lighting conducted from various research shows in Table 5. Various options of the end devices, platform, and application layers can build a complete smart lighting IoT architecture.

4) SMART LIGHTING INTELLIGENCE

Some particular problems in smart lighting have met their solution by applying intelligence. According to Kim and Park [142], intelligent smart lighting is smart lighting that uses AI combined with Internet functions and sensors. Zhang *et al.* [143] applies intelligence to study the lighting connection patterns between light sources and workspace surfaces. While intelligence in the research of Hao *et al.* [144] is using traffic information from lighting. The presented information includes queue length, car speed, and length of the delay. Intelligence can also play a role in system management, reducing manual operations.

The emergence of LED lighting with dimming capabilities and color selection is also fueling the growth of intelligence in lighting. Juntunen *et al.* [145] implements smart street lighting based on movement. LED lighting is an important part of human-centric lighting (HCL), which improves efficiency and convenience. Kwon *et al.* [146] revealed that AI is one of the important elements besides IoT, big data, and cloud technology in the Industry 4.0 emergence. In addition, big companies such as Apple and Facebook are acquiring LED lighting companies and changing their business model in the face of this phenomenon. Karyono *et al.* [36] applies intelligence that focuses on lighting predictions that prioritize comfort in multifunctional rooms. Some multifunctional rooms in the homes of the millennial generation are narrow but practical. As the name suggests, a multifunctional room is a room for various activities where each activity requires a different level of lighting, so it requires intelligence for adaptive lighting.

Intelligent systems are also proven to provide better performance in achieving targets than systems without intelligence. The research produced by Bouzid *et al.* [147] shows that with intelligence, the savings obtained are 77% more significant than without intelligence. Intelligent smart lighting systems can also support larger intelligent systems. Lyubov *et al.* [148] designs intelligent smart lighting that is a part of a smart campus.

Intelligence can also enhance controls in smart lighting. Diaconu [149] says that with the advent of intelligence, manual control is no longer needed. Control via a switch must be replaceable by voice control or control via a smartphone. Kachane [150] reveals that complex rules are needed to regulate lighting by considering several things at once, including presence and lighting. The complexity in question further expands by providing case examples, such as movements that can occur during the day. In contrast, when lighting becomes highly required in the nighttime, special conditions occur when there is no movement. The mentioned schemes cause decision-making errors from a smart lighting system that only relies on a simple rule-based algorithm.

5) RENEWABLE ENERGY AND ENERGY HARVESTING

The issue of renewable energy as a solution arises because fueled energy is increasingly limited. Muhammad and Ali [151] said that renewable energy is essential because energy sources are increasingly limited while demand is increasing. Renewable energy can be a part of street lights because of the giant electricity requirements of street lamps. One of the implementations of renewable energy in smart lighting is to use solar panels. Solar panels can convert light into electrical energy. The use of a switching circuit can stabilize electricity.

In addition to solar panels, wind turbines can also be used for renewable energy, as done by Kiyaki *et al.* [152]. Each module has different characteristics, but if analyzed properly, the combination of the two systems can produce up to 500 W of power. LED lamps are more efficient than conventional lamps, but the savings can increase with the addition of renewable energy solutions.

Arianti *et al.* [153] adds a solar panel solution so that less privileged people can use it by making folk lamps. This folk lamp uses a plastic bottle filled with water mixed with sodium hypochlorite (NaOCl). Installing the bottle in a hole in the ceiling enables natural light to penetrate the hole and propagate through the room.

E. BROADER AND MORE RECENT TOPICS RELATED TO SMART LIGHTING

1) SECURITY

Advanced smart lighting systems connected to the Internet make them vulnerable to cybersecurity attacks. Hofer and Russo [154] analyzes the possibility of cyber attacks on a smart lighting system. The result of the analysis is a list of threats and vulnerabilities. The main goal of a cyber attack on smart lighting is the system's failure. A conceptual tree displays a comprehensive attack taxonomy in which the attack targets include communication, sensing, computing, actuation, and feedback. Examples of attacks on communication are message spoofing and Sybil attacks.

Every vulnerability and security gap needs to address some form of protection. Research conducted by Rajarajeswari *et al.* [155] is an example of an effort to implement security in smart lighting. If used in smart lighting, man-in-the-middle (MITM) attacks can occur on the MQTT communication protocol. Security is used at several network layers to prevent the attack from happening. Transport layer security (TLS) becomes a security option at the transport layer. In addition, the MQTT layer uses Quality of Service (QoS) level 0, which is the QoS with the fastest service, and there is no guaranteed delivery. When unpacking marshaled data from MQTT, an anomaly check is carried out on the data to filter suspicious data. The data goes through an encryption process to secure the system from sniffing attacks on the local area network (LAN).

2) SUSTAINABILITY

Sustainability is a significant factor today. Some circles consider sustainability an ongoing issue and continue to experience management and attention. For businesses, sustainability is vital for environmental factors and affects their core business. Sustainable development goals (SDGs) are 17 global targets proposed by the United Nations (UN) to achieve a better and sustainable future. In the 17 SDG targets, smart lighting is related to the 7th SDG, namely "affordable and clean energy."

Every agency can play a role in sustainability. Mansur *et al.* [156] consider that higher education institutes can play a more significant role in promoting energy efficiency and sustainability by implementing a smart campus. The implementation target of the smart lighting in the smart campus is in the toilets, where fifty-eight motion sensors are present in 30 different toilets, with a production efficiency of up to 77.5%. The contribution of this research to sustainability is the conversion of efficiency to carbon consumption. The resulting efficiency is equivalent to a decrease in gas CO_2 worth 6508 kg.

Besides being applied in cities, buildings, houses, and streets, smart lighting can also become available in warehouses. A warehouse is a strategic place for the implementation of smart lighting because, in the warehouse, lighting energy consumption can reach 65% of the warehouse's total energy consumption. Füchtenhans *et al.* [157] stated that by implementing smart lighting in the warehouse, warehouse emissions decline, and by lowering warehouse emissions, environmental sustainability can take place.

Since sustainability involves a large scale, such as urban development, its implementation and planning also need to be provided on a large scale. Pardo-Bosch *et al.* [158] made a holistic analysis in the form of a value creation ecosystem (VCE) and a city model canvas (CMC) applied to the city of San Sebastian, Spain. The analysis contains the effectiveness, efficiency, and feasibility of any municipality that implements smart lighting for its street light network. A CMC resembles a business model canvas (BMC), including key partnerships, key activities, and value propositions. VCE maps stakeholders as entities, and the flow explains the benefits obtained by each stakeholder consisting of services and cash flow.

Dankan Gowda *et al.* [159] explains more deeply how smart cities, smart lighting, and sustainability are all related to one another. Smart cities are referred to by many as a technology-driven solution, only attractive to technology companies and neglecting the needs of governments, municipalities, and residents. On the other hand, sustainability is concerned with how a city's environment is considered a resource. Sustainability is within reach by finding solutions where the consumption of these resources is in balance with the production of their resources. Pollution of a city must not damage an environment more than the city's ability to supply the environment. When combined, a smart, sustainable city will be born. The key to merging the two is IoT, where the implementation consists of various things related to smart cities and sustainable cities, one of which is smart lighting.

An ideal solution will not be accepted if the idea can not provide tangible benefits. This fact becomes a paradox: these benefits can only happen after implementing the solution idea. To not become a paradox, the proof needs to be done by forecasting. Bachanek *et al.* [160] forecast the implementation of smart lighting to see the benefits of implementing smart lighting. Forecasting looks at the trend of energy consumption. This trend compares countries that do not implement smart lighting with countries that implement smart lighting. Forecasting results show that energy consumption will increase exponentially without implementing smart lighting. On the other hand, sustainability will occur if smart lighting operates. Hence further proving the linkage of smart lighting with sustainability.

3) LED DEVELOPMENT IN COLOR AND BRIGHTNESS

With the presence of LED lighting, users can easily control the intensity and color of the lighting. While computer scientists solve algorithms that effectively and efficiently regulate light intensity and color, physicists think about low-level solutions. Recent research on smart lighting has begun to enter the realm of colorimetry, which is the study of human perception of color. Zandi *et al.* [161] say that it is related to the circadian effectiveness of smart lighting. The circadian cycle or circadian rhythm is a cycle of human activity within 24 hours a day. Circadian lighting is an essential concept in HCL. Lighting based on this circadian cycle refers to its melanopic value. By controlling the light spectrum at a given color, the illuminance can increase by otherwise increasing efficiency. It can take advantage of the non-visual light of the metamer spectra.

Still related to the color of LED lighting, Wang *et al.* [162] expanded the tribo-induced color tuning to evoke purple and pink colors. A wireless-based color activation signal is the concept, and the signal transmits via a smartphone. The resulting prototype can work in seawater monitoring, wind speed monitoring, and speed monitoring between passing vehicles while proposing a novel Triboelectronic nanogenerator (TENG). TENG is a nanoscale electric generator obtained by separating one substance from another. The proposed tribo-induced color tuner has a color inversion plate of $(Sr, Ca)AlSiN_3 : Eu$ phosphor, a tribo-induced liquid lens with chemical formula TiO_2, and a rotary freestanding sliding TENG. The proposed research can provide a self-powered wireless sensor while providing smart lighting with color-tuning capabilities.

The white light from LEDs comes from the excitation of ultraviolet (UV) light or blue light on the surface of the phosphor in the epoxy resin. However, the weakness of phosphor is that it is easily messed up due to heat and can reduce the quality of LED light. Compared to other components in LED lamps, phosphorus has a low thermal conductivity, reducing the life of the LED. Lin *et al.* [163] proposes KNN based lead-free, transparent glass-ceramic to replace phosphor. The complete chemical formula of KNN is $(K_{0.5}Na_{0.5}NbO_3)$. Lead-free ceramic has good thermal stability and high efficiency against heat conduction, so it is a good proposal to replace phosphor.

4) VLC AND SMART LIGHTING CONVERGENCE

LED technology expands the boundaries of smart lighting because it has dimming and color-changing capabilities. Because of the flexibility of LED lighting, dimming can occur in the order of microseconds. With this speed coupled with the speed of light propagation, LEDs can become a wireless communication technology. The technology is called VLC or light fidelity (Li-Fi). The proposal of Katz *et al.* [164] is to bring convergence between smart lighting and VLC. The similarities between smart lighting and VLC are dimming and color control. The difference is the order of time. Because smart lighting is for human convenience, the control of dimming is above the order of seconds or hours, where humans can detect the change. While VLC is communication between lights, communication can be faster. Control for both systems can occur at the same time. Then convergence occurs. In addition, it can include human-light interaction (HLI), which is a light version of human-computer interaction (HCI), or visual communication, the communication between humans and lights, for example, in the form of visual signals. Humans can still catch the signal if it occurs in the order between VLC communication speed and smart lighting communication speed.

Light has a higher frequency than radio. So that if used for communication, light has a bandwidth greater than radio bandwidth. Therefore VLC is used as a 5G communication technology where the bitrate can reach the order of gigabits per second (Gbit/s). In addition, light has other advantages over radio, namely being free of radiation and free of electromagnetic interference. Hu *et al.* [165] uses 443-nm GaN-based superluminescent diode (SLD), discrete-multiple-tone (DMT) modulation, and 256-QAM technology and gets speeds of up to 3.8 Gbit/s. These results make VLC technology more effective for smart lighting.

The survey paper of Mir *et al.* [166] presents some exciting challenges about VLC related to smart lighting. The first challenge was the idea of a self-contained power supply called simultaneous information and power transfer (SLIPT). The wired power supply is impractical, while the battery power supply requires replacements and adds to the hazardous waste. SLIPT can send information as well as energy harvesting as the needed energy. In addition, deployment becomes more concise and more accessible. However, this is related to the next challenge, namely the need for high power for the receiver so that the received data does not become noisy. Another option is to lose the noise while keeping the receiver low in energy. The last challenge is how to obtain directionality if one wants to apply VLC and smart lighting for indoor positioning systems. Lastly is how to remove the field of view (FOV) problem in VLC.

With LED as the technology base, smart lighting and VLC are usable together. There are several places where smart lighting would be difficult to implement using radio-based Wi-Fi, including gas stations, hospitals, and ships. So VLC is the proper substitute in smart lighting systems for these locations. It would be even better if VLC's capabilities were further enhanced. Ali *et al.* [167] offers the concept of multi-input multi-output (MIMO) in VLC. MIMO is a technology for radio technology such as Wi-Fi, WiMAX, and LTE. Its application is in the physical layer by increasing the number of receiving and sending antennas. In addition to increasing speed, MIMO can also expand the range and provide redundancy in delivery to make communication more secure.

5) COMMERCIALIZATION AND ECONOMIC ASPECTS

Smart lighting as a technology is still in the proof of concept stage. Zissis *et al.* [168] puts out a hype cycle like Gartner. VLC, smart lighting, and HCL are still in the technology trigger stage in this hype cycle. IoT and connected light are at the peak of inflated expectations. No technology related to smart lighting is in the trough of disillusionment. OLED is on the slope of enlightenment. Technologies already on a plateau of productivity are LED technology, sensor technology, and ICT technology. Smart lighting and other fields that are still in trigger technology will experience various problems and obstacles in terms of commercialization to reach a plateau in productivity.

As already explained, smart lighting is in the early stage or the technology trigger stage in the hype cycle. Several sub-fields of smart lighting have developed at different times in this phase, as explained in the research of Sun [169]. From 1993 to 2005, research still focused on comparing natural light and artificial light. Research in the years 2005 to 2011 discussed the quality of artificial light. The discussion from 2009 to 2014 is on how to optimize brightness. From 2012 to 2014, the correlated color temperature (CCT) value became an important value in smart lighting, while the discussion was on optimizing the CCT value. In 2016, the issue was the application of a context-based lighting system.

Various demands are directed to smart lighting to show the technology's worthiness to be diffused in society and become a prospective and successful business. Baharudin *et al.* [170] conducted a review showing several comparisons between smart lighting and the existing building management system (BMS). Smart lighting shows some disadvantages but also some advantages compared to BMS. The benefits of existing BMS are low cost, while smart lighting has a high price. In addition, because the BMS does not connect to the Internet, it is more secure against cyber attacks. However, in other aspects, smart lighting is superior to BMS. Its advantages include low energy consumption, automatic operation, easy monitoring, and error detection without human intervention.

The prospect of the smart lighting business in attracting corporates needs demonstration with an objective and short return on investment (ROI). Shankar *et al.* [171] explains the economic analysis in more detail by comparing the cost of smart lighting plus photovoltaic (PV), aka solar panels, with conventional electricity from the grid. Initially, smart lighting + PV will be more expensive than the grid because of the investment spent on smart lighting, PV, and products installation. Nevertheless, gradually, the cost of smart lighting + PV will decrease. The results are from PV having a surplus of electricity to cover the expenses incurred to pay for the grid. At some point, there is no electricity expenditure at all, which is called zero net energy.

On the other hand, the initial cost of the grid is low because there is no investment. However, grid costs will constantly increase due to routine electricity expenditures. At some point, the initial lower cost of the grid will outweigh the smart lighting + PV. That point will occur within five years. Further on, smart lighting + PV produces 47.89 GWh in 25 years and reduces greenhouse gas by 46941 Kg from the environment.

In research commercialization, technology acceptance is a crucial element to research. Kim *et al.* [172] analyzed the technology adaptation of the elderly to smart lighting. This research aims to understand the lighting conditions needed by the elderly and environmental issues related to lighting faced by the elderly. The survey conducts on 57 respondents who are members of a nursing home with an average age of 83.74 years with an average mobility awareness and good health. The results show that, on average, they think that lighting lacks areas for activities such as reading, writing, watching TV, and other hobbies. The cause conveyed was the wrong lamp placement and poor lamp control ability. The survey results concluded that the technology needed for respondents was smart lighting, smart curtain, and activity recognition.

IV. MACHINE LEARNING IN SMART LIGHTING

This section answers the second research question of the paper survey, which explores smart lighting papers that apply one or more machine learning methods in solving smart lighting problems. The discussion revolves around what methods are involved, how machine learning categorizes these methods, and how each method can help smart lighting.

Zantalis *et al.* [173] said that the more IoT devices installed, the more data related to sensors emerge. With more and more data, many applications have sprung up to draw correlations between data and make decisions. This case led to the emergence of AI and machine learning in smart lighting. There are many methods in machine learning, each with a different purpose, and the results of the survey paper show that there have been many studies on smart lighting that apply various machine learning methods.

A. MACHINE LEARNING METHODS

Figure 6 shows the smart lighting research taxonomy concerning the machine learning method used. Implementable strategies are the second leaf from the tip. There are four main machine learning types: classical learning, reinforcement learning, ensemble learning, and deep learning. Deep learning is a subset method of machine learning where a model already includes feature extraction and selection [174]. Deep learning's ability to perform its feature extraction and selection is called feature learning [175]. The sub-categories of deep learning include deep neural network (DNN), convolutional neural network (CNN), and recurrent neural network (RNN). One of the RNN methods is long short-term memory (LSTM). Classical learning is all methods outside the deep learning subset, which it divides into two large families: supervised learning and unsupervised learning. The supervised learning method divides into classification and regression, where classification methods include Nave Bayes, support vector machine (SVM), KNN, Logistic Regression, and Decision Tree. Then regression methods include linear regression, support vector regression (SVR), and ANN regression. Unsupervised learning is used, among others, for clustering and dimension reduction. The clustering methods include k-means and DBSCAN.

In comparison, dimension reduction methods include principal component analysis (PCA). Reinforcement learning methods include Q-learning, deep Q-learning network (DQN), genetic algorithm (GA), and particle swarm optimization (PSO). Ensemble learning can be divided into bootstrap aggregating (bagging) and boosting. Bagging methods include random forest, while boosting methods include adaptive boosting (AdaBoost) and XGBoost.

1) SUPERVISED LEARNING

Sepponen *et al.* [176] explain that supervised learning is a learning model where the expected output of each input has a term. The termed result is usually called a label or class. The class can be categorical or numerical, furtherly dividing the supervised method into classification and regression methods [177].

In supervised learning, the **classification** method is a method of categorizing a data set into several classes. Examples of classification methods in supervised learning are ANN classification [29], decision tree, SVM, KNN, naïve Bayes, and logistic regression.

ANN emulates the structural, biological, and functional features of a biological neural network (BNN) [178]. ANN consists of various neurons that optimally connect the inputs and outputs in a dataset by several calculations. Each neuron node has an input and output process. The input and output processes act upon the following formula

An ANN model containing a series of artificial neurons results from a training process. ANN training regulates the weight of each neuron in the ANN model iteratively until the model becomes optimum. The following is the Weight formula in each training iteration

$$W_{ji}(n+1) = W_{ji}(n) + \delta W_{ji}(n) \tag{1}$$

where W is the weight, i is the source neuron index, j is the destination neuron index, and n is the iteration number.

The way to measure the optimum level of an ANN model is to calculate the error. The error is the difference between the predicted and actual values. The formula for calculating

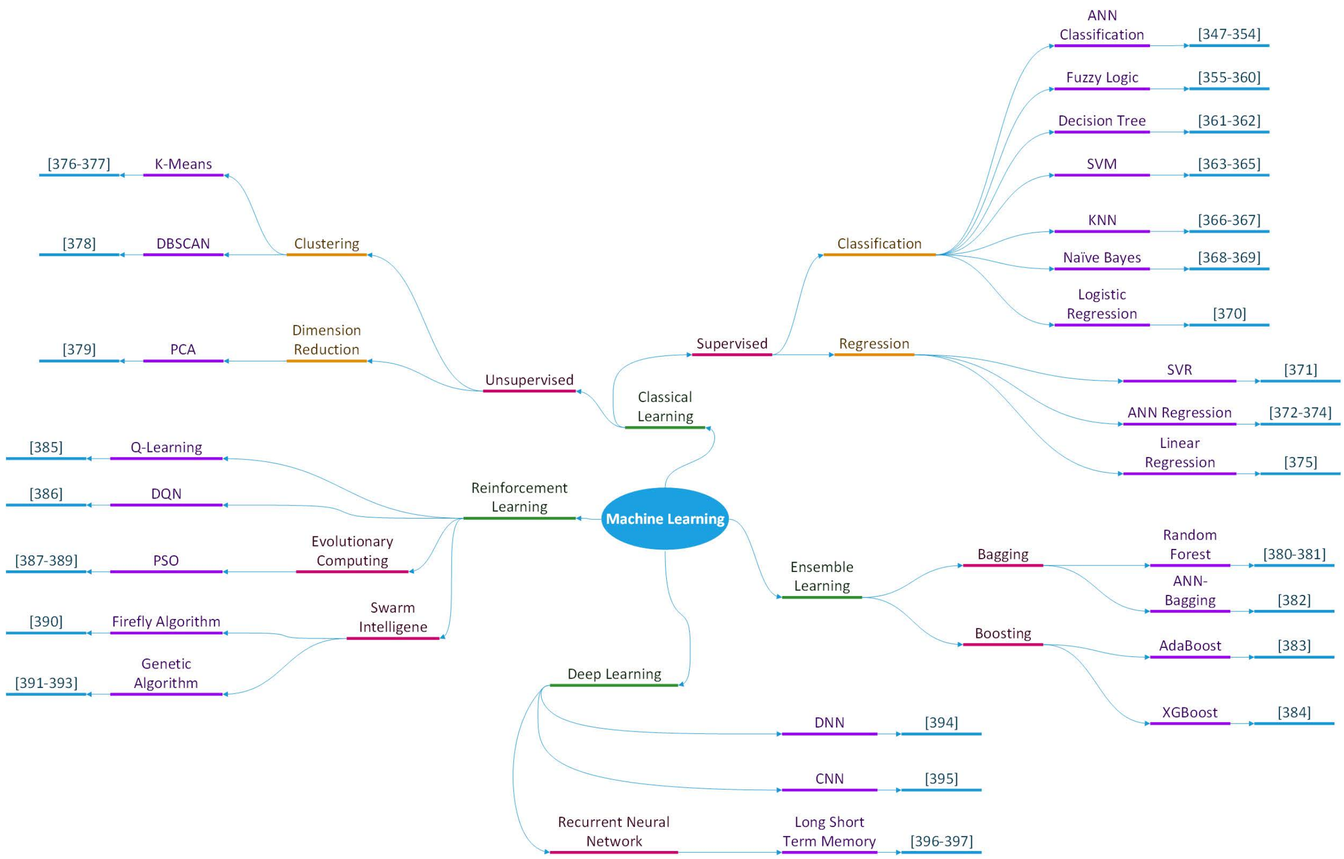

FIGURE 6. A mind map that explains the categories of each machine learning method and reference papers related to each machine learning method.

the error in each iteration n is as follows

$$E(n) = \frac{1}{2}\sum_{j=1}^{M} e_j(n)^2 \tag{2}$$

where $E(n)$ is the error in n iteration, M is the number of output neurons, and $e_j(n)$ is the difference between the output and actual values.

In the training process, several metrics need to be considered, namely epoch, learning rate, and momentum [179]. In addition, the number of neurons in the input layer, the number of hidden layers, and the number of neurons in each hidden layer can also vary to obtain the optimum model [180].

Regarding the application of ANN in smart lighting, Mohandas *et al.* [181] uses the ANN method with fuzzy logic for decision-making in smart lighting control. This study collected data through light, motion, and PIR sensors. By applying ANN as decision-making, unwanted lighting can reduce by 34% and the savings obtained are 13.5%.

Decision Tree is a decision-making model that resembles a tree, where the tree is formed from the result of training [182]. Several methods are available to construct a decision tree, including iterative dichotomiser 3 (ID3) and classification and regression tree (CART) [183]. ID3 can only be used for classification, while CART can also be used for regression [184]. In ID3, tree formation goes through several stages, some of which calculate entropy and the information gain. The formula to obtain the entropy, $E(S)$, is as follows

$$E(S) = \sum_{j=1}^{k} -p_j log_2 p_j \tag{3}$$

where S is the dataset, k is the number of classes, and p_j is the probability of occurrence of class j. Then the gain formula is as follows

$$Gain(A) = E(S) - \sum_{i=1}^{k} \frac{|S_i|}{|S|} \times E(S_i) \tag{4}$$

where A is the class, k is the number of categories in the class, and S_i is the occurrence probability of category i in the class.

SVM is a margin-based classification method [185]. The classification method is to train a hyperplane that can separate data. In making the hyperplane, several available kernels include radial basis function (RBF), polynomial, sigmoid, and linear [186]. In a kernel polynomial of degree-d, the formula is as follows

$$K(x, x_i) = (x_i x + 1)^d \tag{5}$$

where x and x_i are vectors in the input space. Then the classification function, $f(x)$, is by the following formula

$$f(x) = \sum_{i=0}^{n} a_i y_i K(x, x_i) + b \tag{6}$$

where a_i is the value of the Lagrange multiplier, y_i is the y value of x_i, and b is the intercept.

KNN is an algorithm that performs classification by looking at the similarity of the data, for example, with Euclidean distance [187]. The similarity of the data in question calculates the distance from a data to other datasets in the database. The following formula calculates the distance

$$Distance(x, y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2} \tag{7}$$

where x is the classified data, y is the training data, and n is the number of dimensions or features.

Naïve Bayes is a classification based on the Bayes theorem. It is a theorem that looks at a new event's hypothesis probability [188]. It is efficient because it takes the assumption that attributes are independent [189]. The naive Bayes classification formula is as follows

$$P(c|x) = \frac{P(x|c)P(c)}{p(x)} \tag{8}$$

where x is the data with an unknown class, c is the hypothetical data of a particular class, and $P(c|x)$ is the posterior probability c based on x [190].

Research on SVM and naïve Bayes are present in smart lighting. Xu *et al.* [191] used and compared SVM and naïve Bayes to classify street light conditions using the light sensor on a smartphone. Three different light attributes were present in the study, where from each attribute, its mean and standard deviation emerge from extraction.

In addition to the methods already mentioned, **logistic regression** is also a method available for classification. Logistic regression is a type of regression method, but it is handy to analyze the binary or categorical relationship between several factors that influence each other [192].

Regression is a method in machine learning that is applicable to predict a continuous relationship of the dependent variable to the independent target variable [193]. Among the existing regression analysis methods, the simplest and most commonly used way is **linear regression** [194]. The formula for linear regression is as follows

$$Y = \beta_0 + \beta_1 X_i \tag{9}$$

$$\beta_0 = \frac{(\sum y)(\sum x^2) - (\sum x)(\sum xy)}{n(\sum x^2) - (\sum x^2)} \tag{10}$$

$$\beta_1 = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x^2)} \tag{11}$$

where Y is the dependent value, X_i is the independent value, β_0 is the intercept, β_1 is the slope, i is the member of the independent variable, and n is the size of the dataset [195].

Modifications of the classification methods are also applicable for regression. Instead of using voting to choose the suitable class, KNN regression uses local average [196] calculations. Then the name of the regression method of SVM is SVR. ANN regression is like ANN classification, but instead of categorical, the output is numeric dependent [197].

Regression is present in recent research on smart lighting. Vikash *et al.* [198] compares KNN regression, SVR, and linear regression to predict the set point of smart lighting control. Boter-Valencia *et al.* [199] uses ANN regression to replace the role of spectral power distribution (SPD) to measure light quality at a low price. Beccali *et al.* [200] uses ANN Regression to map the luminaries measured on the sensor, i.e., on the ceiling, against the luminaries on the workbench.

2) UNSUPERVISED LEARNING

The main difference between unsupervised learning and its counterpart is that it does not require any predefined labels in the training [201]. With these differences, the task of unsupervised learning diverges from classification and regression. Because it does not make predictions on labels or outputs, unsupervised learning is more directed to find patterns between the training data [202]. Hence, unsupervised learning tasks include clustering and dimensionality reduction.

Clustering is finding natural grouping in a data set [203]. Clustering can also be called automatic classification, wherein in the classical classification, a label must be present if, in clustering, the label can be created by itself [204]. K-means and DBSCAN are two examples of clustering methods.

K-means is a distance-based clustering technique [205]. The purpose of using distance for clustering is to reduce data variance. Before the clustering process begins, the value of K or the number of clusters must be determined first. Then the centroids are randomly assigned according to the value of K. The next process is to calculate the distance of another point to each centroid point using equation (7). Clustering will gather the points to the nearest centroid. The process is repeated continuously with the new centroid obtained by calculating the mean of each cluster. The repetition will stop after convergence occurs. That is, there is no change in the mean. The whole process repeats with the initiation of a new centroid. Then each process is compared. The selected process is the process with the smallest amount of variance. Here is the formula to find the variance of a process

$$Variance = \frac{1}{m_k} \sum_{i=1}^{m_k} ||x_i - \mu_k||^2 \tag{12}$$

where k is the cluster index, m_k is the number of data in cluster k, x_i is the i^{th} data in the cluster, μ_k is the average of k clusters [206].

Like k-means, **DBSCAN** is also a distance-based clustering method. The difference is that the weakness of k-means is that it is susceptible to noise in the data, while DBSCAN has a way to detect noise [207]. DBSCAN is present in recent smart lighting research. Ravi *et al.* [208] uses DBSCAN to cluster the pixel values of a camera to get the lux value of each cluster.

The curse of dimensionality is a problem where a dataset has too many features. In other words, it has high *dimensionality*. Such datasets can experience various issues, as they cannot be reasoned and analyzed by humans who are used to dealing with 3-dimensional space [209]. **Dimension reduction** is a method to reduce the number of dimensions or the number of data features with high dimensionality while maintaining the valuable properties of the original data [210]. One of the dimension reduction methods is principal component analysis (PCA).

Suppose there is a data table with size nxp, where n is the number of rows, while p is the number of columns, then **PCA** considers it as matrix X [211]. Next, PCA creates a new feature with notation t by multiplying the line $x_{(i)}$ of X by weight w and size l, where l is a smaller number than p [212]. The PCA formula is as follows

$$t_{k(i)} = x_i \cdot w_k \tag{13}$$

where $i = 1, \ldots, n$, and $k = 1, \ldots, l$. The value of w is set so that the PCA results have a variance not distant from the X matrix.

3) REINFORCEMENT LEARNING

If supervised learning and unsupervised learning are analogous to "learning by reading," then reinforcement learning is equivalent to "learning by doing" [213]. The five main reinforcement learning components are agent, environment, action, reward, and state, where an agent interacts with the environment by performing actions. The action will change the state of the environment. A reward measures the quality of the state change. The reward will determine the following action of the agent [214].

One implementation of reinforcement learning is **Q-learning**. Q-learning takes action based on a policy that utilizes the Markov Decision Process (MDP) [215]. MDP is an extension of the Markov chain, where the difference is that in MDP, there are actions, and their state changes by a policy function that determines which action will be chosen by a state in the transition to the next state [216]. While the policy function will change based on the reward of the state transition. The optimal policy function is as follows

$$\pi_*(a|s) = \begin{cases} 1, & \text{if } a = \text{argmax}_{a\in A} q_*(s,a), \\ 0, & \text{otherwise,} \end{cases} \tag{14}$$

where $\pi_*(a|s)$ is the optimal policy function, a is the action, A is the action set, s is the state, and $q_*(s, a)$ is called the optimal action-value function. The formula for the optimal action-value function is as follows

$$q_*(s,a) = \max_\pi q_\pi(s,a) \tag{15}$$

$$q_\pi(s,a) = R_a^s + \sum_{s'\in S} P_{ss'}^a \sum_{a\in A} \pi(a'|s') q_\pi(s',a') \tag{16}$$

where $q_\pi(s, a)$ is the action-value function, R_a^s is the reward on state s and action a, s' is the next state $P_{ss'}^a$ is the state transition probability matrix, and a' is the next action.

There have been studies using reinforcement learning in smart lighting. Yu *et al.* [217] uses a reinforcement learning method called deep deterministic policy gradient (DDPG) to find the optimum decision based on several parameters that have uncertainty. DDPG is a method that combines operation over continuous action space from the deterministic policy gradient (DPG) method with experience replay and slow learning target network from the deep Q-network method (**DQN**).

4) ENSEMBLE LEARNING

Ensemble learning combines several machine learning methods into one, where usually, the performance results will be better than any of its ensemble members used alone. This method is considered a state-of-the-art method in the field of machine learning [218]. However, the drawback of ensemble learning is that by combining several methods, the algorithm will be more complex and become more computationally heavy [219]. The two main sub-categories in ensemble learning are bagging and boosting.

Bagging stands for bootstrap aggregating, which is the two main stages of bagging itself. An example of a method that uses bagging is random forest [220]. Bootstrap is a method of replicating multiple datasets from the main dataset using a sampling method [221]. Furthermore, the method creates a weak classification method for each dataset. A process similar to voting for the final classification runs on several weak models. Namely, the aggregating method [222].

Random forest is an ensemble learning method that utilizes many weak decision trees with the bagging method. The random forest can solve the decision tree problem, namely overfitting. Overfitting usually occurs if the resulting tree has a too large depth, traditionally characterized by a significant variance. In a random forest, by maintaining a small depth but increasing the number of trees, the random forest can reduce the variance while maintaining the bias [223].

The random forest method is present in recent smart lighting research. Zekic-Susac *et al.* [224] implements a random forest on the smart lighting system using big data from the system. Data from the big data system that becomes features for the classification process are geospatial attributes, construction attributes, heating attributes, temperature attributes, and occupational attributes. The predicted output is energy consumption.

If bagging can reduce variance, then **boosting** is an ensemble learning that can reduce bias [225]. While bagging is parallel because it creates many classifiers at the same time, boosting is serial because every weak classifier will be affected by the previous weak classifier [226]. The way boosting works is by increasing the weight of the miss-classified data in the previous classifier to the next classifier and then reclassifying the data [227]. The final classifier is a linear combination of the previous classifiers [228].

One of the boosting methods is **AdaBoost**. AdaBoost is also an ensemble learning method that can be applied to the decision tree and is used to overcome the class imbalance in the decision tree with the concept of boosting [229]. The AdaBoost formula is as follows

$$F_T(x) = \sum_{t=1}^{T} f_t(x) \tag{17}$$

where x is the input data, $F_T(x)$ is the final classifier, T is the number of estimators or the number of weak classifiers, and $f_t(x)$ is the t$^{\text{th}}$ decision tree.

5) DEEP LEARNING

In classical learning, to perform classification, datasets usually experience dimensionality problems and must go through the feature extraction and feature selection stages first [230]. The difference with deep learning is that it already conducts these stages in its model. The stage is called feature learning, or representation learning [231]. Sub-categories of deep learning that exist in recent smart lighting research are deep neural network (DNN), CNN, and recurrent neural network (RNN).

DNN is an ANN that has more than one hidden layer [232]. DNN can be used to predict complex non-linear functions better than traditional methods and techniques [233]. When compared to ANN, the more data there is, the better the performance of DNN, while ANN will reach saturation point faster with less data [234].

CNN is a deep learning method that is often used for object detection in computer vision [235]. In training a CNN model for an image, gradient descent is applicable to find the local minimum of the loss function [236]. The convolution and spooling functions in CNN are what make CNN superior in image processing because it pays attention to the locality of reference problems that other neural network methods do not do [237]. Thus causing other neural network methods to experience the curse of dimensionality problem [238].

RNN is deep learning that can deal with temporal sequences because RNN has an internal state (memory) that can store information from the current input to deal with future inputs recursively [239]. Due to the temporal nature of the sequence, RNN is suitable for handwriting recognition or speech recognition. [240]. Two examples of RNN methods are long short-term memory (LSTM) and gated recurrent units (GRU).

What makes **LSTM** distinctive from other RNN methods is that this method has special units. The special units are cell, input gate, output gate, and forget gate [241]. The three gates can control the cell's contents to forget which information, add new information, and output what information. Thus, the LSTM does not just use memory to remember the previous state like a standard RNN.

B. MACHINE LEARNING APPLICATIONS IN SMART LIGHTING

After discussing the categories and machine learning methods present in recent smart lighting research, the following subsection discusses applications of machine learning methods in smart lighting. Some machine learning applications in smart lighting are more common than others. They are discussed individually in this section. Because this paper directs the discussion on smart lighting that can increase user comfort, we also carry out a critical review on which application is suitable for increasing user comfort. Table 6 shows the extraction results of machine learning application topics in smart lighting.

1) PREDICTIVE CONTROL

Predictive control is one of the control methods applied in industrial engineering [270]. Predictive control or model predictive control (MPC) is a sophisticated control that can predict the performance of a process based on the future horizon [271]. The prediction horizon is the extent to which a model can predict the future [272]. The model is used to predict the future based on training data and then take control to deal with predicted future events [273]. The autoregressive integrated moving average (ARIMA) and LSTM are methods that are applicable in predictive control [274].

Predictive control is one of the machine learning applications present in recent smart lighting research. Yang *et al.* [275] utilizes predictive control in controlling smart lighting, air conditioning, ventilation, and shading in an integrated manner. Two test areas were ready to test the system, one where the proposed method was present and one room with the old system. Two metrics predicted in this system are visual comfort and lighting power. Predictive control can also predict maintenance time for street lighting, as done by Gălăţanu *et al.* [276].

2) INTELLIGENT CONTROL

Intelligent control is the use of AI techniques or machine learning in traditional control systems to deal with more complex problems [277]. For example, a control system has inputs such as temperature, humidity, light level, and carbon dioxide level sensors. Then they combine with outputs of fans, coolers, heaters, and lights. Methods such as ANN can be applied to predict the proper control for each actuator based on various values of input sensors [278].

Intelligent control is one of the machine learning applications present in recent smart lighting research. Intelligent control in the research of Shnayder *et al.* [279] uses lighting sensors, motion sensors, and traffic intensity sensors to control street lighting. Chew *et al.* [280] defines the target of smart lighting control, namely brightness, gain, hysteresis, timeout, and sampling period—the output control results from the combination of the user presence and brightness targets. As for Sakaci *et al.* [281], the intelligent control of the proposed smart lighting uses fuzzy logic.

TABLE 6. Machine learning applications in recent smart lighting research.

Topic	ML Method Basis	Characteristics	Improvement Goal	References
Predictive Control	ANN	Time series-based classification and forecasting	Energy efficiency	[242] [243] [244] [245] [246] [247] [248]
Intelligent Control	SVM, ANN	Close loop control with intelligence	Energy efficiency	[249] [250] [251] [252] [253] [254]
Hand Gesture Detection	ANN, SVM, random forest	Smart lighting control with hand gesture and IMU sensors	User experience	[255] [256] [257]
Clustering	DBSCAN, k-means	Feature clustering with scatter plot	Color clustering, sensor efficiency	[258] [259]
Anomaly Detection	ANN	Classification on smart lighting network anomalous data	Security performance	[260] [261]
Measurement Calibration	LSTM, random forest	Regression-based learning to increase illuminance measurement	Measurement accuracy	[262] [263]
Optimization	PSO, Genetic Algorithm	Use of evolutionary computation in optimization	Optimum value of comfort and energy effeciency	[264] [265]
Computer Vision	CNN, DNN	Camera based smart lighting control	Energy efficiency	[266] [267]
Activity Recognition	ANN	User movement based smart lighting control	Energy efficiency, user comfort	[268] [269]

3) GESTURE RECOGNITION FOR CONTROL

Gesture recognition is a computer science technique to detect human gestures with mathematical algorithms [282]. Gesture recognition usually includes emotion recognition involving face and hand gesture recognition [283]. Hand gesture recognition usually involves a wearable type sensor. An inertia measurement unit (IMU) sensor is applicable because it has the function of an accelerometer and a gyroscope [284]. Hand gesture recognition is usable as an advanced control in a non-haptic human-machine interface (HMI) where users no longer need to use switches or conventional remote controls [285].

Hand gesture recognition is one of the machine learning applications applied to smart lighting. Park *et al.* [286] said that hand gesture recognition is vital in smart lighting to get the full functionality of the proposed system. Mohammed *et al.* [287] utilizes smart clothing, namely wearable sensors attached to clothes, as a medium for executing gesture recognition. Pham *et al.* [288] also propose hand gesture detection, but it depends on cameras, not wearable sensors. Chen *et al.* [289] also use a camera to detect hand gestures. In addition, this study utilizes the SVM classification on the history of gradient (HOG) features to determine the type of gesture to form a figure of eight or show five fingers.

4) CLUSTERING

Clustering is an unsupervised learning method to form classes based on adjacent data. Clustering is a machine learning application present in recent smart lighting research. Hoque *et al.* [290] uses K-Means clustering to classify the characteristics of energy consumption by smart lighting users. The results show two main clusters in energy consumers by optimizing the number of clusters. Three main features separate the two clusters, namely total energy, energy in the ironing room, and energy in outdoor lighting.

Borile *et al.* [291] uses clustering to reduce the number of datasets. The problem is in the proposed method, namely regression with weighted least squares. Each processing of new data requires the formation of a new matrix, where the complexity and computational time will increase with the presence of a new matrix. So the k-means++ method is used to reduce the number of datasets. This method can reduce the risk of overfitting.

5) ACTIVITY RECOGNITION

The primary process of activity recognition is to detect high-level user activity from raw sensors [292]. The implementation of activity recognition is diverse, including in the fields of smart home, sports, billing automation, elderly monitoring, security, and gaming [293]. For example, in the healthcare sector, activity recognition is used for the care of the elderly or the maintenance of physically impaired patients [294]. In the field of security, activity recognition is applicable to determine the desired level of home security [295].

Activity recognition is one of the machine learning applications present in recent smart lighting research. Kookmin *et al.* [296] implements smart lighting that performs control based on the user's location in a room.

The implementation of a location-aware lighting system is to increase user satisfaction. Juntunen *et al.* [297] issues lighting controls based on the movement of people in the room captured from Kinect. The system built can control the intensity of light and the type of color based on user preferences.

6) ANOMALY DETECTION

Anomaly detection is the detection of rare data whose presence raises suspicion because the data is very different from the usual data [298]. Anomaly detection is implementable in intrusion detection systems (IDS), fraud detection, medical anomaly detection, industrial anomaly detection, or time-series anomaly data [299]. Some types of machine learning are usable in anomaly detection. Unsupervised learning is used by clustering all normal data into one cluster. Data that are not inside the cluster are labeled as an anomaly [300]. Anomaly detection with supervised learning treats anomaly problems like binary classification, where the first class is normal data, and the second class is anomaly data [301].

Anomaly detection is one of the machine learning applications employed in smart lighting. Gao *et al.* [302] uses anomaly detection to detect suspicious movements captured in surveillance cameras. This research adopts AdaBoost to classify anomalous actions and non-anomaly actions. The camera is pointed at the stairs to monitor going up and down activities at the stairs. In the future, lighting will be implementable in the system for mitigation.

7) OPTIMIZATION

When dealing with non-linear objective functions, advanced methods need to be applied. Optimization is a method of finding the best results based on an objective function and several restrictions to get valid results [303]. Optimization applications include smart grids, logistics, and WSN. Several machine learning methods that are usable as optimization methods are Bayesian network, reinforcement learning, and Q-learning [304].

Optimization is one of the machine learning applications implemented in machine learning. Ndzana *et al.* [305] uses GA to optimize between getting the maximum light intensity with primary colors and getting the maximum savings. The result is that the intensity complies with standards, while the most significant savings come from red's primary color. Ngo *et al.* [306] compares GA with an exhaustive search in finding the most optimal lighting in a room. The result is that with the same level of savings, GA can find optimal lighting faster than an exhaustive search.

8) COMPUTER VISION

Computer vision is a technique for obtaining a high-level understanding of the [307] image or video. The advantage of using computer vision in smart lighting is that advanced control of smart lighting can take advantage of CCTV cameras which are usually already installed in an area [308]. The stages in computer vision can include object acquisition, feature extraction, classification and analysis, and disseminating results [309]. Several methods in feature extraction that are applicable include Gaussian filter and RGB color extraction [310].

Computer vision is one of the machine learning applications in smart lighting implemented. Cho *et al.* [311] uses deep learning utilizing services from IBM Watson to understand what kind of food an occupant is eating in a smart lighting system. The camera used is a Raspberry Pi camera placed above the dining area. The lighting will adjust to the type of food the occupant is eating. Mortadha *et al.* [312] controls the lights based on face detection implemented on the camera. Maciel *et al.* [313] implements PCA in Eigenface face recognition as authentication in smart lighting. The concept of ''space of face'' and PCA are usable in Eigenface face recognition.

9) ELDERLY MANAGEMENT

With the increasing number of older adults in the world, more technology is needed for elderly care [314]. Some of the applications of these technologies are fall detection, localization, and health status monitoring. The role of smart lighting is to make life easier for the elderly whose movement is increasingly limited [315]. Several environmental sensors play a role in this aspect, including magnetic switches, PIR sensors, and floor sensors [316]. Davis *et al.* [317] implements SVM-HMM to adjust the color and intensity of the lights based on the detected elderly activity. The length of the elderly activity influences the lamp's intensity, and the type of activity affects the lamp's color. There are six activities detected, namely walk, up, down, sit, stand, and lay [318]. The accuracy result of the proposed system is 99.7%.

V. TOPICS IN INCREASING USER COMFORT

This section answers the third research question of the paper survey, which selects and explores machine learning implementations that are promising in achieving user comfort. The discussion includes examining activity recognition as an encouraging method in increasing user comfort and delving into user comfort parameters from related papers.

A. IMPLEMENTATION OF ACTIVITY RECOGNITION

Adnan *et al.* [319] say that insufficient lighting can interfere with health, and lighting must be adjusted based on activity. Kookmin *et al.* [296] state that there are two reasons for smart lighting, energy efficiency and comfortable lighting. For the second reason, lighting awareness of activities becomes a requirement. In the activity recognition method, machine learning plays a role in extracting activities from raw data obtained from [320] sensors. Several processes must run to transform raw data into activity types, namely feature extraction and classification. The activities types can be categorized based on their complexity levels. The whole activity recognition process, starting from sensing to activity classification, can be seen in Fig. 7. The following is a complete explanation of the activity recognition stages.

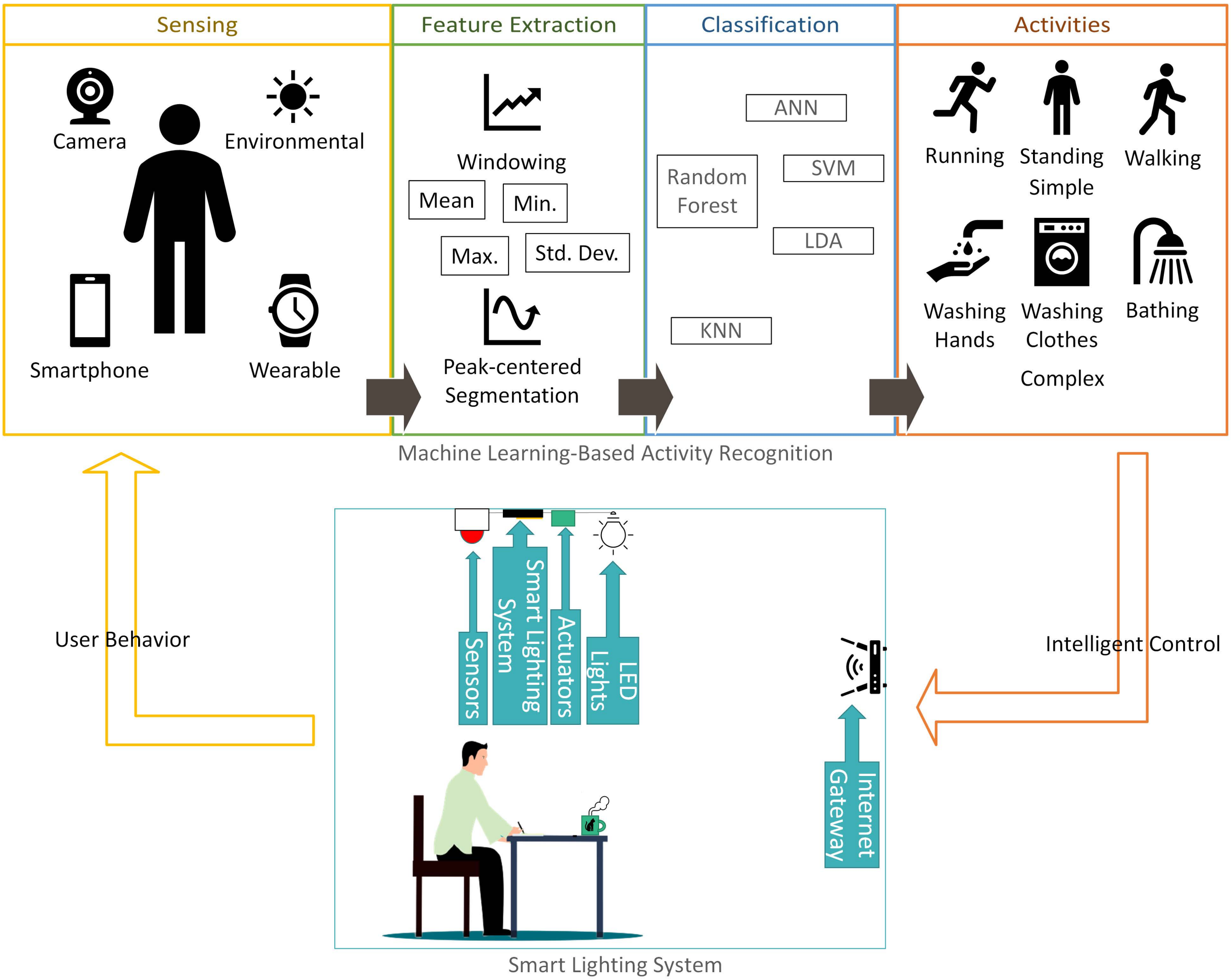

FIGURE 7. The integration of a smart lighting system and machine learning-based activity recognition that promotes intelligent user behavior control while potentially increasing user comfort.

Within the sensor types used to collect sensor data, there is a taxonomy [321]. Firstly, sensing is divided by video-based or sensor-based technology [322]. Kushwaha *et al.* [323] combines discrete wavelet transform (DWT), local binary pattern (LBP), and histogram of gradients (HOG) in **video-based** activity recognition. The video dataset comes from five different sources: Weizmann, IXMAS, UT Interaction, HMDB51, and UCF101. Besides being implemented on publicly available datasets, the methods also run on real-time datasets. The real-time dataset originates from a Bollywood movie.

Sensor-based types split up into environment-based, wearable-based, and smartphone-based. **Environment-based** activity recognition uses ambient sensors placed in the room, as is done by Guan *et al.* [324] which uses a PIR sensor. PIR sensors can only detect motion with the concept of infrared radiation changes (IRC). However, activity patterns show by changing the feature-specific sensitivity. Feature-specific sensitivity can increase by changing the visibility modulation on the geometric sensing layer. There are two types of mounting used during deployment: a ceiling mount and a tripod mount. In the simulation, one ceiling mount locates in the middle of the room, with three tripod mounts on the sides of the room.

Wearable-based activity recognition is a method in which the sensor used comes from a device attached to the user's body, for example, a smartwatch that takes data from the wrist, as done by Mekruksavanich *et al.* [325]. The smartwatch used is an Android smartwatch with LG G Watch and Android Wear 1.5 operating system. Embedded in the smartwatch are accelerometer and gyroscope sensors. The smartwatch dataset comes from the public benchmark, namely WISDM, obtained from the UCI Repository. The dataset contains tri-axial accelerometer data and tri-axial gyroscope

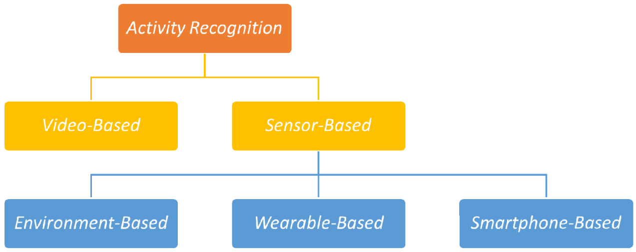

FIGURE 8. Activity recognition taxonomy based on sensors.

data with a sampling rate of 20 Hz. The data subjects were 51 people with an age range of 18 to 25 years and 18 types of activities that have been pre-labeled.

Smartphone-based activity recognition is on sensors provided in smartphones. Voicu *et al.* [326] researched activity recognition utilizing existing sensors on smartphones such as accelerometer, gyroscope, and gravity sensor. Two datasets in use were: the internal dataset and the external dataset. The internal dataset came from a self-made application designed for the research, and the external dataset came from a dataset from another research. The user first selects the activities before the data recording in the self-made application. The choice is between walking, running, sitting, standing, and going upstairs or downstairs. In addition, the measurement interval and sampling rate are also adjustable. Users can choose which sensors to activate for measurement as an additional option.

A complete taxonomy of sensor types in activity recognition shows in Figure 8.

Information about human activities is usually hidden in sensor data, so a **feature extraction** [327] process is required. Lupion *et al.* [328] developed environmental sensors-based activity recognition and implemented a sliding window to combine multiple sensor sources at once. Of the values in each window, the extracted features are the minimum, maximum, and average values. Ferrari *et al.* [329] first performs a peak centered segment of the time-series data from the accelerometer sensor and then performs a feature extraction. Eighteen features were extracted, including minimum, maximum, mean, median, and standard deviation. The 18 features reduce into two features with PCA.

After performing feature extraction, these features go through a training process to form an **activity prediction model**. Jung and Chi [330] uses the ANN model to predict activity based on sound sensor data. Dewi and Chen [331] compares random forest, SVM, KNN, and linear discriminant analysis (LDA) methods for the activity classification. The results of this study indicate that random forest is superior to other methods.

In addition to applying a combination of feature extraction and classification, deep learning methods can be used and already cover both steps. Xia *et al.* [332] compares three deep learning methods, namely LSTM, CNN, and a combination of LSTM and CNN. Predictions run on three different datasets with six movement classes. The results showed that the combined LSTM-CNN was better than the other two methods.

In a survey paper on activity recognition, Demrozi *et al.* [333] revealed that there is a taxonomy related to detectable activities. Detectable activities consist of simple and complex activities. **Simple activities** such as walking, running, sitting, and getting up, as in the research of Zheng *et al.* [334]. **Complex activities** are washing dishes, watching TV, eating, and cooking, as classified by [335].

Table 7 compares the latest research related to activity recognition in the field of smart lighting. The similarity of each study is that they have applied activity recognition to smart lighting, whether using video-based, environment-based, or wearable-based sensors. However, each research show contradiction in the performance and accuracy. Some research shows high performance in predicting activity recognition. However, require high-cost devices for recognition. On the other hand, other research that uses low-cost tools can provide only sub-optimal results.

The research of Dai *et al.* [338] proposes a video-based activity recognition for smart lighting that has a high level of accuracy. Nevertheless, on the other hand, in terms of hardware, the use of the camera is very extensive. Five cameras from different angles are needed to get such accuracy. On the other hand, Ramadhan *et al.* [337] also has an accuracy above 90% but not as good as Dai *et al.* However, the solution is not extensive and uses a WSN where each node uses a low price PIR sensor. Zhao *et al.* [344] proposes wearable-based smart lighting that uses Google Glasses for sensing. The research is not feasible from the solution considering the price of google glass and the inefficient implementation. However, camera-based and environment-based smart lighting are possible methods for smart lighting.

One of the classification methods in activity recognition for smart lighting is the hierarchical hidden Markov model (HHMM) method proposed by Ramadhan *et al.* [337]. HHMM is an extension of the hidden Markov model (HMM). Figure 9 shows an example of an HHMM model that can run on a smart lighting system. A conventional HMM model consists of 3 layers, where the first layer is the initial state. The initial state gives the initial probability for each hidden layer. The second layer is the hidden state, which are states that are not observable. It is necessary to go through the observable states to discover the present hidden state. State transitions between hidden states show the probability of state changes from one period to another. In HHMM, there can be more than one hidden state. The higher hidden layer needs to be observable to discover deeper hidden layers. In the implementation of smart lighting, the observable state is the sensor value, hidden state 2 is the activity, and hidden state 1 is the lamp status.

Furthermore, the Viterbi algorithm determines the hidden state from the observable state. Viterbi algorithm formula for the first prediction and the following predictions are different. The formula that describes Viterbi's algorithm for the first

TABLE 7. Comparison of activity recognition in recent smart lighting research.

Proposal	Type	Sensors	Classification	Pros	Cons
Sigurdson *et al.* [336]	Video-based	Camera	RestNet18	High accuracy	Limited activity
Ramadhan *et al.* [337]	Environment sensor-based	PIR Sensor	HHMM	Low price	Limited accuracy
Dai *et al.* [338]	Video-based	Camera	Pixel-wise	Efficient algorithm	Extensive use of camera
Chun *et al.* [339]	Video-based	Depth camera	Proximity-based	High accuracy	Expensive sensors
Sharma *et al.* [340]	Video-based	Camera	KNN	The use of low-spec cameras	Low accuracy
Byun *et al.* [341]	Environment sensor-based	PIR Sensor	Movement-based	Achieved energy efficiency	No report on movement accuracy
Huber *et al.* [342]	Environment sensor-based	Pressure mat, PIR Sensor	None	Comprehensive for elderly use	Conceptual, no algorithm proposed
Afshari *et al.* [343]	Environment sensor-based	Color sensor, ToF Sensor	Light transport model	Use of advanced sensors	Does not implement sensor fusion
Zhao *et al.* [344]	Wearable-based	Google Glasses	PCA	Comprehensive architecture	Inefficient solution
Lee, et. al [345]	Wearable-based	Accelerometer	HMM-Decision Tree	Delay efficient	Some inaccurate results

prediction is as follows

$$V_{1,k} = P(y_1|k) \cdot \pi_k \tag{18}$$

where k is the number of hidden states, π_k is the value for the initial state transition probability to hidden state k, $P(y_1|k)$ represents the probability from hidden state k to the first observable state, and $V_{1,k}$ represents the Viterbi value for k.

The formula that describes Viterbi's algorithm for subsequent predictions is as follows

$$V_{t,k} = \max_{x \in S} P(y_t|k) \cdot a_{(x,k)} \cdot v_{t-1,x} \tag{19}$$

where $V_{t,k}$ represents the t$^{\text{th}}$ Viterbi value for k hidden states, $v_{t-1,x}$ represents the highest previous Viterbi value, $\max_{x \in S} P(y_t|k)$ describes the highest transition value from hidden state which is the previous highest Viterbi value to hidden state k, $a_{x,k}$ is the value from hidden state k to observable state t.

B. USER COMFORT METRICS

Table 8 shows the latest research on smart lighting that discusses user comfort. The similarity of each study is that they pay attention to at least one aspect of user comfort in using smart lighting. However, each research is contradictory in how to measure user comfort. Because user comfort is related to humans, some measurements are subjective. That is, they are calculated based on user opinions. In addition, other metrics are objective measurements that focus on technical aspects of smart lighting comfort.

Plorer *et al.* [356] say that control strategies in smart lighting usually focus on user comfort or energy efficiency. So there are two parameters in implementing smart lighting: energy efficiency and user comfort. Measuring energy efficiency can be done by calculating the energy consumption of a smart lighting system. The equation is as follows

$$Energy(Wh) = Power(W) \times Time(h) \tag{20}$$

So that the greater the power of the electrical equipment used and the longer the electrical equipment is in use, the greater the energy spent.

In calculating user comfort, Light Utilization Ratio (LUR), Unmet Comfort Ratio (UNC), and Light to Comfort Ratio (LCR) are applicable. The LUR formula is as follows

$$LUR = \frac{\text{Time With Lights On}}{\text{Occupied Time}} \tag{21}$$

From the formula above, the optimal LUR value is 1. If it is more than 1, it concludes that the lights are on longer than they should be. Meanwhile, if the value is between 0 and 1, it can be supposed that the lights are on less than they should. While the UNC formula is as follows

$$UNC = \frac{\text{Time in Uncomfortable Condition}}{\text{Occupied Time}} \tag{22}$$

The range of UNC value is 0 to 1. The closer to 0, the better the smart lighting performance. Then the LCR formula is as follows

$$LCR = \frac{1}{n} \sum_{t=1}^{n} Score(t) \tag{23}$$

where n is the number of tests and $Score(t)$ is obtained from the definitions as follows

$$Score(t) = \begin{cases} 0, & \text{if user is uncomfortable,} \\ 0.5, & \text{if user is unsure,} \\ 1, & \text{if user is comfortable.} \end{cases} \tag{24}$$

The LCR value is the sum of each person's $Score(t)$ results, then averaged by the total amount of tests. Each person can

TABLE 8. User comfort test parameters in recent smart lighting research.

Parameter	Alias	Example Use Case	Type	Range	Optimum Value	Used in
LUR	Light Utilization Ratio	Occupant centric building performance metric	Objective	0 to ∞	1	[346] [347]
UNC	Unmet Comfort Ratio	Energy Standard for building	Subjective	0 to 1	0	[348] [349] [347]
LCR	Light to Comfort Ratio	Smart lighting with reinforcement learning	Subjective	0 to 1	1	[347]
PRR	Power Reduction Rate	Smart lighting with SCADA	Objective	0 to 100%	As minimum as possible with maximum power reduction	[350]
Flickering perception		Dimming without causing flickering	Subjective	0 to 100%	0%	[351]
Kruithof ís comfort curve		LED context lighting system	Objective	2000 to 7000 (K) with 0 to 10000 (Lux)	Inside the pleasing area	[352] [353]
CCT	Correlated Color Temperature	Comfort in Indoor LED lighting	Objective	2000 to 100000 K	Follows a Gaussian function	[353]
% Recommended Luminance		Smart lighting with BMS	Objective	0 to 100%	100%	[354]
Relative MSE	Relative Mean Square Error	Adaptive smart lighting control	Objective	0 to ∞	Lower than Reference sensor MSE	[355]

give response multiple times. The range of $Score(t)$ values is 0 to 1. The closer to 1, the better the smart lighting performance.

From existing research, user comfort can be grouped based on the measurement object and its measurement type. The user comfort parameter can be divided based on control and lighting quality based on the measurement object. Measurements based on control quality observe whether the control decisions in determining the on/off state of smart lighting interfere with user comfort. Measurements based on lighting quality see whether the brightness or the color of the light interferes with user comfort or not. LUR is an example of user comfort measurement based on control quality because the measure refers to the ratio of the time the lights are on with the time the lights are used [347]. Flickering perception is an example of user comfort, which is calculated based on the lighting quality [351].

User comfort parameters divide into objective and subjective parameters based on the measurement type. LUR, Power reduction ratio (PRR), and CCT are three objective parameters because they result from measurements. PRR is calculated based on the value of the power to be reduced [350]. CCT is a measurement of the color temperature of a light [353]. CCT correlates with the subjective value of user comfort, which is mapped based on a Gaussian function. It makes CCT a good objective measurement method to predict user comfort based on lighting quality. LCR is an example of a subjective parameter because it comes from a questionnaire.

VI. OPEN ISSUES AND FUTURE WORK

This section contains a critical review of discussed papers in answering the three research questions of the survey paper. The result is the discovery of research gaps for opportunities in future works.

Based on the reviewed studies, smart lighting started in 1993, starting from lighting combined with a microcontroller to applying machine learning in smart lighting. Several survey papers have discussed smart lighting, but none have comprehensively addressed the application of machine learning to smart lighting. Based on the survey, several studies have implemented machine learning in smart lighting, including the topic of intelligent control, gesture recognition for lighting control, and clustering for optimizing sensor placement in WSN smart lighting. Activity recognition is a suitable method to increase user comfort because it pays attention to user activities in light control. Discussions about research gaps are possible in the state-of-the-art (SOTA) papers studied.

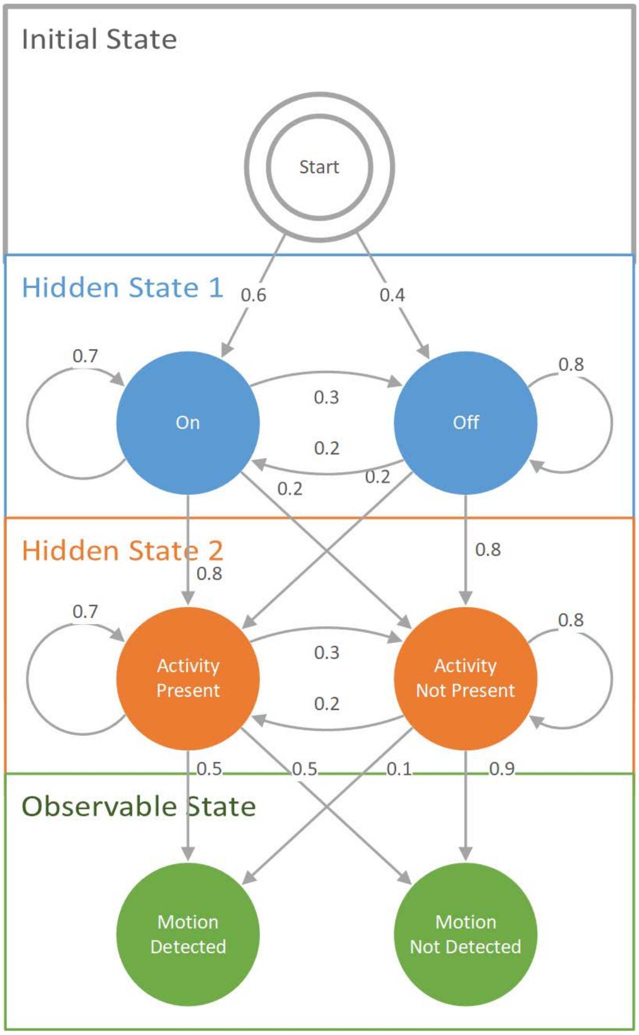

FIGURE 9. An example of a HHMM model in activity recognition for smart lighting.

A. COST AND EFFECTIVENESS

Activity recognition is a suitable method to increase user comfort because it pays attention to user activities in light control. Several studies regarding activity recognition in smart lighting are present. Among the existing studies, several solutions provide high activity prediction accuracy but, on the contrary, have extensive and expensive hardware specifications. On the other hand, researchers that provide a low price solution report limited movement prediction accuracy.

The key to a successful IoT project is the initial cost and scalability [357]. An affordable price is essential to widely spread an IoT solution in the market. Several studies have proven that combining a low-price device with a good performance algorithm can optimize the solution. Abate *et al.* [358] uses a cheap current sensor, namely a shunt resistor, combined with the Goertzel algorithm, which has good accuracy on smart grids. Nawandar and Satpute [359] use soil moisture, temperature, and humidity sensors and a controller with a total cost of US$ 13 combined with the ANN method for a smart irrigation solution. Sunny *et al.* [360] said that solutions in nuclear waste monitoring are usually expensive, then offer a cheap solution using gas sensors and AI for decision making and has good performance.

The research gap is how to produce an activity recognition solution for smart lighting that is not extensive and low in price but has high activity prediction accuracy by utilizing state-of-the-art machine learning techniques.

B. OPTIMIZING THE MACHINE LEARNING METHOD

In choosing the machine learning method with the best performance, comparisons are considerable. Each machine learning method has its advantages and disadvantages. Therefore, each technique has a different implementation area. A comparison of the advantages and disadvantages of machine learning methods shows in Table 9.

Machine learning methods have advantages and disadvantages and can excel in different studies. Naïve Bayes can excel if used in the field of sentiment analysis or web crawling [412], [413]. Meanwhile, if used for classification based on sensor values, SVM and decision trees can be superior to naïve Bayes.

Dimension reduction methods such as PCA can improve classification performance by enhancing features. Omuya *et al.* [414] prove that by comparing four different scenarios, data that has gone through the PCA process has the best performance. Apart from improving performance, PCA can also shorten training time and reduce memory usage. Research from Ma and Yuan [415] shows that with PCA, training time can reduce from 1300 s to 100 s, and memory usage can decrease from 6133 MB to 1000 MB.

The use of ensemble learning can also solve various problems in machine learning. Random forests can improve classification performance while reducing overfitting problems. The research of Dogru and Subasi [416] shows that the performance of random forest classification is better than SVM and ANN. The use of AdaBoost can overcome the problem of data imbalance. Taherkhani *et al.* [417] prove that the performance of the AdaBoost-CNN classification model on the imbalance dataset is better than using ResTNet.

Several advantages of deep learning are useful in activity recognition for smart lighting. Complex human activities have a hierarchical structure that can take advantage of the multiple layers in deep learning. Chen *et al.* [418] reveals that deep models can learn descriptive features from complex sensor data. In addition, automatic feature extraction in deep learning has a better performance than manual feature extraction. Shaheen *et al.* [419] have specifically tested the comparison of automatic feature extraction and manual feature extraction, and the results show that classification with automatic feature extraction leads to better performance.

By applying and comparing various classification methods, combining several methods with ensemble methods, or using unsupervised learning methods for pre-processing, novel activity recognition methods with significantly higher performance in smart lighting applications can emerge.

TABLE 9. Comparison of machine learning techniques in smart lighting.

Category	Subcategory	Method	Strength	Weakness	Paper
Supervised learning	Classification	ANN Classification	Versatile	Black box model	[361] [362] [363] [364] [365] [366] [367] [368]
		Fuzzy Logic	Transparent model	Manually adjusted	[369] [370] [371] [372] [373] [374]
		Decision Tree	Transparent model	Suffers from over-fitting	[375] [376]
		SVM	Good for data with separate classes	Underperforms in data with noise	[377] [378] [379]
		KNN	No training time	Problems in dimensionality	[380] [381]
		Naïve Bayes	Good for small dataset with logic premise	Zero frequency problem	[382] [383]
		Logistic Regression	Able to classify dependent data	Bad on data with no linear correlation	[384]
	Regression	SVR	Good for data with separate classes	Underperforms in data with noise	[385]
		ANN Regression	Versatile	Black box model	[386] [387] [388]
		Linear Regression	Easy to implement	Assumption on linearity	[389]
Unsupervised learning	Clustering	K-means	Simple clustering	Bad on noisy data	[390] [391]
		DBSCAN	Resistant to noise	High dimensionality problem	[392]
	Dimension reduction	PCA	Improves features	Low interpretability	[393]
Ensemble learning	Bagging	Random forest	Solves overfitting	High complexity	[394] [395]
		ANN-Bagging	Reduces variance	High complexity	[396]
	Boosting	AdaBoost	Solves data imbalance problem	Bad on noisy data	[397]
		XGBoost	Good on small data	Bad on sparse data	[398]
Reinforcement learning	Model-Free	Q-Learning	Adaptive method	Slow on sparse reward	[399]
		DQN	Faster training	Overestimation of Q-values	[400]
	Swarm Intelligence	PSO	Simple concept	Easy to fall into local optimum	[401] [402] [403]
		Firefly Algorithm	Small number of iteration	Easy to fall into in local optimum	[404]
	Evolutionary Computing	Genetic Algorithm	Good for optimization	Computationally expensive	[405] [406] [407]
Deep learning	DNN		Automatically tuned features	High complexity	[408]
	CNN		Good for image processing	Lots of training data required	[409]
	RNN	LSTM	Good for sequences of data	Takes longer to train	[410] [411]

C. TIME CONSTRAINT AND DELAY MEASUREMENTS

Because the smart lighting system is a real-time system, there is a time constraint in its implementation [420]. The application of machine learning can improve system performance in predicting efficiency and user comfort. However, the delay caused by the algorithm's complexity must still be suitable. Jobanputra *et al.* [421], in research on activity recognition, said that generally, simple algorithms have a short runtime but poor performance. In contrast, complex algorithms have a long runtime but better performance.

The random forest can improve accuracy, but the algorithm's complexity also increases because it uses many classifiers. Tests conducted by Garcia and Korhonen [422] prove that as the number of estimators in the random forest model increases, the runtime also increases exponentially. AdaBoost has even a higher complexity than random forest. Toghani and Allen [423] shows that the AdaBoost runtime is more elevated than random forest in all 13 datasets used for testing. The number of estimators must be optimum, i.e., where the performance increases but with a minimum number of estimators. Deep learning methods such as CNN can make it easier to improve feature performance through the initial layers but, on the other hand, increase complexity with heavy algorithms. Arif *et al.* [424] prove that with a similar performance in computer vision, CNN has a higher time delay compared to simple methods such as Haar-Cascade.

Reinforcement learning methods may be engaging because they are adaptive and can find the optimum solution or achieve convergence. However, the weakness of reinforcement learning is that it is challenging to earn optimal rewards when the rewards are sparse. There can be a long lag before the user gets the optimum reward if applied in smart lighting. Research conducted by Zhong *et al.* [425] shows that deep learning can reach convergence in 30 episodes while reinforcement learning reaches convergence in more than 150 episodes.

Each real-time system has a different time constraint. Suppose an effective but complex method has a higher runtime than other methods. The method is still acceptable if it falls within the time constraint, especially if the comparison method has unacceptable performance.

D. SENSOR SELECTION AND COORDINATION

If activity recognition with one type of sensor may experience performance limitations, an option to consider is to use multiple sensors at once. Considering the cost, this is still feasible by combining several inexpensive sensors at once. Combining several sensors simultaneously to get better detection results is known as sensor fusion. Aguileta *et al.* [426] through the survey paper on sensor fusion, revealed that combining several different sensors has better performance than combining several of the same sensors. Environment-based sensor fusion has never been applied to smart lighting and could become a research opportunity.

In environment-based recognition, achieving activity measurements from one sensor to one user with good performance are already challenging, all the more if the implementation is in one room with several sensors and several users. Li *et al.* [427] divides activity recognition into single-user activity recognition (SAR) and multi-user activity recognition (MAR). SAR has made some advancements in its research. However, research in MAR is still at a very young age. MAR with environment-based sensors is challenging because the detected activities are very complex. In a multi-sensor environment, activity detection becomes challenging because the user's movement from one sensor range to another can be difficult to detect.

E. ANOMALY DETECTION ON FAULTY SENSORS AND RAMS ANALYSIS

If implemented on a large scale, wherein one large room can be installed with up to 80 smart lighting devices, and each tool performs sensing, it is likely that some tools have poor performance due to faulty sensors. Detection of poor tooling must occur at the manufacturing stage to prevent user complaints during installation. Faulty sensor detection is a current research trend in the IoT field. Van *et al.* [428] uses anomaly detection to find faulty sensors in connected and automated vehicles (CAVs) in the build phase.

Anomaly detection on the faulty sensor can also occur during installation, namely after manufacturing goods. Zhang and Li [429] applies anomaly detection to faulty sensors in urban sensing at the installation stage with the assumption that damage can occur due to external factors from the environment. Keipour *et al.* [430] detects measurement errors on the automated aerial vehicle (AAV) during air travel, assuming the aircraft can be landed in an emergency when there is early detection in the air. Ellefsen *et al.* [431] detects anomalies in an autonomous ferry machine prognostic and health management (PHM), which detects odd occurrences to the ship's engine. Salem *et al.* [432] detects an anomaly in the health monitoring wireless body sensor network (WBSN) by measuring the RMSE between the measured sensor value and the forecasted sensor value. Despite anomaly detection in faulty sensors in various IoT fields, we have not found any research implementation on smart lighting. It can become a research opportunity for future work.

Petrioli *et al.* [433] implemented reliability, availability, maintainability, and safety (RAMS) analysis in reducing the possibility of excessive spare parts procurement for upscaling a smart street lighting system. The study exercises two methods: reliability analysis and failure mode, effects, and criticality analysis (FMECA). Our exhaustive study of machine learning techniques can lead to a more efficient solution for RAMS analysis. Brandl *et al.* [434] provide an example use of embedding sensitivity analysis into avionic virtual sensors with the use of neural networks. However, a machine learning solution for similar cases on smart lighting is still a research gap.

F. OBJECTIVE AND SUBJECTIVE MEASURES IN USER COMFORT

There is room for expansion of user comfort measurement parameters in smart lighting. The most significant characteristic of smart lighting compared to artificial lighting, in general, is carrying out controls that automatically turn on and off lights. Where user comfort in artificial lighting generally only detects the quality of light, both in intensity and color. Park *et al.* [347] admits that the comfort measurement in their research is limited to illuminance and should expand towards glare, color rendering index, light color, and flicker. Nagy *et al.* [349] say that the limitations of the test sample can reduce the quality of the conclusions drawn from user comfort. User comfort testing should also be carried out within a year because different seasons will provide other lighting qualities. According to Wang *et al.* [353], Kruitoff's Curve is only a quantitative assessment of user comfort and is not accurate. Some of Kruitoff's Curve's review of illuminance does not match the applied retest. Illuminance has a low multiple analysis of variance (MANOVA) value on user comfort, so it is not usable as a performance measure. Although there is a strong correlation between CCT and user comfort, it turns out that user comfort in several countries is different and needs further evaluation. In addition, user comfort based on other locations, for example, at home, office, and factory, needs to be studied further.

An objective measurement with a high correlation to its subjective measurement counterpart can result in an effective tool for predicting user comfort. The research of Park *et al.* [347] has used both objective and subjective parameters for user comfort measurement based on lighting control in their research. However, it did not map the correlation between the two. In addition, Wang *et al.* [353] concluded that CCT is a good tool to predict user comfort but only in the field of lighting quality. There is still a gap to find objective measurements for predicting user comfort based on lighting controls.

There is no existing research on activity recognition smart lighting that measures user comfort. They can become a research gap for further research. Using user comfort measurement, the significance of implementing activity recognition in smart lighting compared to legacy methods can become visible. Research on smart lighting that measures user comfort has also left a research gap for future works.

VII. CONCLUSION

This study provides a comprehensive survey on smart lighting and proposes SLR to discuss the application of machine learning in smart lighting to increase user comfort. Machine learning as part of artificial intelligence provides key solutions in overcoming complex problems in smart lighting. These include predictive control, intelligent control, hand-gesture recognition for lighting control, clustering, anomaly detection, calibration, optimization, computer vision, and activity recognition. An exhaustive review of improving user comfort covers discussions, such as the methodology and taxonomy of activity recognition as a promising solution and user comfort metrics, including light utilization ratio, unmet comfort ratio, light to comfort ratio, power reduction rate, flickering perception, Kruithof 's comfort curve, correlated color temperature, and relative mean square error. Finally, we discuss open issues and future challenges in increasing user comfort in smart lighting using activity recognition.

We have discussed the challenges in increasing user comfort with smart lighting with activity recognition where low-price and extensive solutions differ significantly in prediction performance. An affordable price is essential to widely spread an IoT solution in the market. The optimum solution can combine a low-price device with a good performance algorithm. The optimum machine learning algorithm can be achievable by comparing various classification methods, combining several methods with ensemble methods, or applying unsupervised learning methods for pre-processing. Another challenge discussed in this paper is the concern of time constraints in a real-time system, where effective but complex methods have higher runtime than simple methods with several limitations. In addition, existing user comfort metrics applied to smart lighting research can be used in the novel activity recognition method to prove the significance of contribution.

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