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Thammasat AI City Distributed Platform: Enhancing Social Distribution and Ambient Lighting

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Abstract. The Thammasat AI City distributed platform is a proposed AI platform designed to enhance city intelligent management. It addresses the limitations of current smart city architecture by incorporating cross-domain data connectivity and machine learning to support comprehensive data collection. In this study, we delve into two main areas, that is, monitoring and visualization of city ambient lighting, and indoor human physical distance tracking. The smart street light monitoring system provides real-time visualization of street lighting status, energy consumption, and maintenance requirement, which helps to optimize energy consumption and maintenance reduction. The indoor camera-based system for human physical distance tracking can be used in public spaces to monitor social distancing and ensure public safety. The overall goal of the platform is to improve the quality of life in urban areas and align with sustainable urban development concepts.

Keywords. AI City, smart city, social distribution, city ambient lighting, AI platform

1. Introduction

As cities continue to grow and become more connected, there is an increasing need for advanced technologies such as artificial intelligence (AI) to manage and optimize the complex systems that make up a modern city. One area where AI can have a significant

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impact is in the field of smart cities, where AI can be applied to improve the quality of life for residents and make cities more efficient and sustainable. As technology advances and the cost of sensors and network devices decreases, the concept of the Internet of Things (IoT) is becoming more feasible. Cities are able to use digital infrastructure and high-speed communication to connect various devices and systems, allowing for greater data collection and analysis, and improved efficiency and decision-making. This is the place where artificial intelligence and machine learning come into play to maximize data's value. Machine learning can be used to process the large amounts of data generated by connected devices in the IoT which can lead to more efficient and effective decision-making. Machine learning can also be used to optimize the performance and energy efficiency of connected devices and systems, and to improve the accuracy and reliability of their data. In conjunction with the data streaming from various possible sources including IOT devices, to a platform and the analytic results from machine learning, the data-driven artificial intelligence is well-suited to form the analytical foundation of the AI City.

Thammasat AI City initiative is an determined program that aims to establish a resilient AI platform at the Rangsit campus of Thammasat University. The initiative focuses on four key domains, including elderly and healthcare, mobility, environment, and economy. It is designed to identify the opportunities and challenges of AI disruption and to create a role model for the full activation of data and physical availability. The Rangsit campus location is an ideal setting for the project as it allows for testing AI solutions in a real-world scenario and involving multiple stakeholders. The initiative aligns with the societal changes and technology trends that have emerged in the wake of the COVID-19 pandemic, namely distributed city, human traceability, new reality, home-office integration, contactless technology, digital lending, and frugal innovation. The goal of the initiative is to create a model for a smart city that is efficient, sustainable, and responsive to the needs of its citizens.

The remainder of the paper is organized as follows. Section 2 discusses the issues in the challenges of urbanization. Section 3 explains the architecture and design of the AI City initiatives. Section 4 elaborates on the AI City domain specific connectivity with the proposed technologies. And the conclusion in Section 5.

2. The Challenges of Urbanization

Thammasat University, Rangsit Campus is one of the leading universities in Thailand, known for its research and education programs in various fields including agriculture, economy, politics and science. The Rangsit campus is situated in Pathum Thani province, a city near Bangkok, where covers an area of 1,526 square kilometers. The city has a population of 985,643 according to a 2020 report of the National Statistical Office of Thailand. It serves as an important hub for higher education, hosting ten renowned universities, Thailand Science Park and seven mega economic areas which includes shopping malls and agricultural markets. And 35.11 percent of the total land area are the agriculture area.

Similar to many cities in Thailand, Pathum Thani Province is facing a rising population situation. This increase in population is accompanied by a number of urbanization problems, such as insufficient elderly care facilities, environmental deterioration, and traffic congestion. These issues can have a negative impact on the overall quality of life for the inhabitants of the province. With the reference of the

Pathum Thani City Planning 2018 – 2022 by The Pathum Thani Provincial Office (2018) [1], the urbanization of Pathum Thani brings with it the potential for a surge in various issues and hurdles. These encompass challenges like heightened traffic congestion and road safety concerns, a rise in environmental issues, economic and tourism-related troubles, as well as shifts in lifestyle patterns. To address their challenges, it is important for the local government and community to work together to develop sustainable solutions that balance the needs of the growing population with the preservation of the environment and quality of life for residents. This may include efforts to improve public transportation, promote sustainable development, and increase access to healthcare and other services. Additionally, encouraging the creating an efficient solid waste management system, developing of the capabilities of the target industries, social development and basic security of the people can help to mitigate the negative impacts of urbanization on the environment and economy.

3. AI City Initiatives

The Thammasat University's AI City networking in RUN project is an initiative to model AI capacity on a city scale within the Rangsit campus, which is 2.8112 square kilometers in size. The project aims to address the current limitations of AI research caused by the insufficiency and diversity of data. Reliable and connected data will be collected and made available to demonstrate AI's capabilities in real-life applications fully. The project functions as a based-platform [2] for four high-impact domains in Rangsit city, including healthcare, environment, mobility, and economy. The project is equipped with various AI-enabled devices namely healthcare monitoring devices [3], noninvasive bed sensors [4], environmental sensors, video analytics cameras, street lights, indoor tracking devices [5], and drones for aerial photography. Figure 1 depicts the architecture of the AI City platform and its cross-domain connectivity.

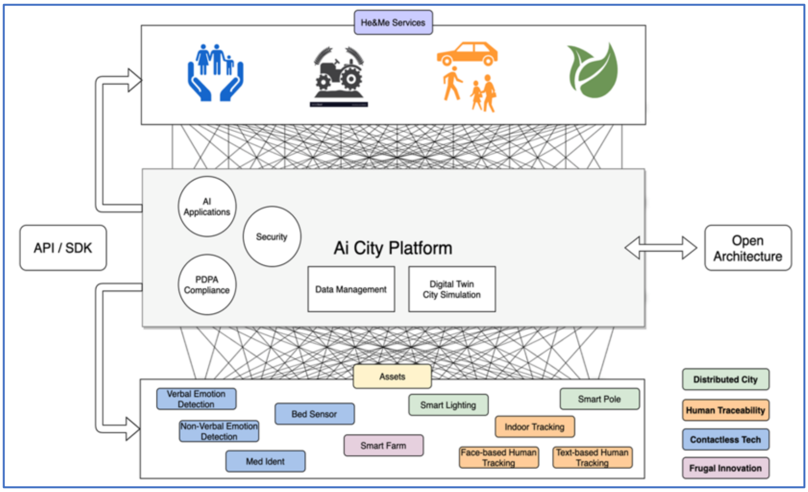

Figure 1. AI City platform architecture and cross-domain connectivity.

In order to make the data from several sources available for modeling, the data is stored and sent to the cloud services using low energy mesh network (6LoWPAN protocol in case of smart lighting, Bluetooth low energy (BLE) in case of indoor positioning and bed sensor, etc.). To reduce the high bandwidth consumption devices such as video streaming of surveillance cameras, LAN connectivity, and several techniques[2] (steady state at rest, motion detection, etc.) are introduced. In addition, bed sensors for elderly care systems, the detection of types of on-bed position is localized not only to realize the real-time warning but also to conserve the bandwidth by sending the compressed results to the cloud.

The AI City Project is a comprehensive approach to integrate AI into city operations and infrastructure through four main layers: the accumulation layer, the knowledge layer, the understanding layer, and the decision-making layer, as illustrated in Figure 2. Data from IoT devices is analyzed and connected to produce models and prediction results in four targeted domains. The primary layer is the layer of accumulating physical raw data through various sensor network devices as the foundation for the subsequent layers. The next layer is data extraction into knowledge and once the knowledge has been created with new coming data, we can make good understanding and provide good decision at the final layer by the advance of deep learning, neural network and machine learning. Model training for specific tasks is conducted in the understanding layer. The appropriate machine learning paradigms are introduced and evaluated to produce the results in the decision-making layer. The connectivity and selection of the data from various sources are crucial to implementing in the city-scale AI platform development. The platform composes of health & aging care platform, environment platform, mobility platform and economy platform [6].

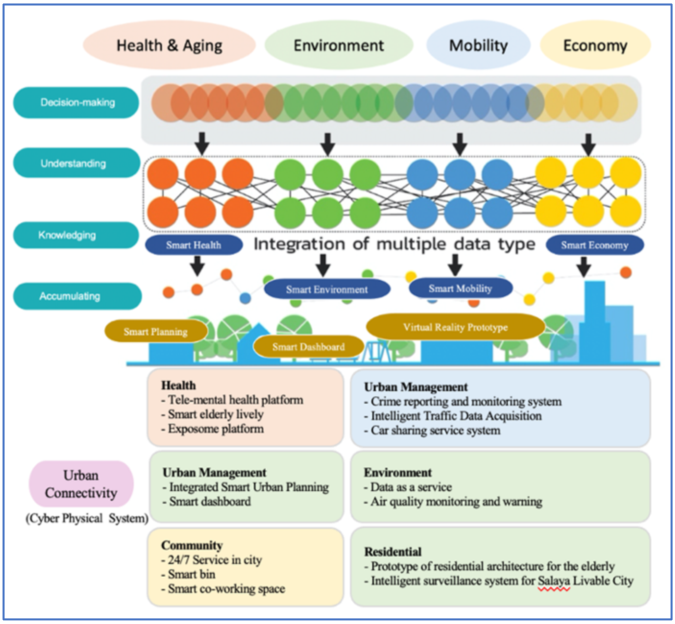

Figure 2. Deep intelligent IoT in fully connected network.

[2] https://info.verkada.com/surveillance-features/bandwidth/

3.1. Smart Health and Aging Care Platform

As Thailand transitions into a fully aged society, with 10% of its population being over 60 years of age, significant demographic changes are underway. The project aims to address the growing burden of caring for the elderly. It seeks to improve the quality of life and access to health care services for communities near Thammasat University, focusing on five areas: social, activity, health, medicine, and sleep condition. The project involves the development of a technology-based health platform for the aging population, consisting of five main components. Those are the sleep quality analysis system, the medicine identification system, the indoor positioning and services system, the daily health monitoring system, and the elderly follow-up and care robotic system.

3.2. Smart Mobility Platform

Centered around the Thammasat University Rangsit Campus and Pathum Thani Province, this platform holds the objective of elevating mobility, curbing air pollution, enhancing safety, and fostering tourism through the analysis of travel trends and the provision of comprehensive insights. The platform encompasses three key components: an intelligent traffic data acquisition system, a car sharing service system, and a crime reporting and monitoring system.

3.3. Smart Environment Platform

The smart environment platform is strategically designed to tackle environmental challenges and contribute to the overarching objective of smart city development. This platform harnesses the capabilities of IoT technologies and AI systems to vigilantly monitor the urban environment. Anchored in the principles of urban environment monitoring, the platform encompasses pivotal systems including the monitoring of air pollution levels, a weather forecasting system, and a vehicle front camera-based inspection system designed to identify suspicious objects.

3.4. Smart Economy Platform

The Thammasat University Rangsit Campus and Pathum Thani Province are home to various educational and research organizations, including AIT and NSTDA, that conduct research in various fields. However, there is a lack of promotion and connection between these organizations and the private sector. Thus, a Smart Economy Platform is being developed to connect these organizations and bring research results to real-life applications. This will involve collaboration between research universities and researchers to improve innovation and foster cross-disciplinary and geographic cooperation. Leveraging the power of big data and Deep Learning, this platform is poised to analyze and process information. Its core objective is to facilitate collaboration between the public and private sectors. Moreover, it aspires to enhance the domain specific service value and productivity, cultivate specialized industries and services, and bolster local entrepreneurship. This comprehensive approach involves integrating research with real-world challenges, aiming to bring about tangible advancements.

4. AI City Domain Specific Connectivity

Regarding to the domain specific connectivity, there are four types of technology that we focus on, namely distributed city, human traceability, contactless technology and frugal innovation. In this paper, we will mainly focus on the distributed city and the contactless technology.

As countries around the world try to admit that the Covid-19 has evolved a strain to survive, to be able to spread easily and quickly until eventually many countries have to accept that COVID-19 is an endemic disease. From trying to block the border to minimize the spread. As well as efforts to eradicate this disease within a limited time at the cost of enormous social and economic losses. Finally, we have to adapt and learn to live safely with COVID-19 and have as much balance in life as possible. From the concept of new normal that our way of living moved to relied on the online communities, it was currently changed to the next normal. Although epidemic prevention measures are sparse, the lives of people have changed a lot from the original.

Covid-19 changes our behaviors and attitudes in life, especially the exposure to technology including the online platforms which meets the needs of convenience, safety, and hygiene. These behaviors are leading to the next normal way of living which impact to the economy and environment in the future. People are aware of safety, stability, and more flexibility in living and of a greater understanding that health is fundamental to life. The stay-at-home economy, touchless society, physical distancing, and elevating health and wellness concern are concrete examples of the next normal.

Although the situation has improved. But there is still no vaccine that is 100 percent effective in preventing infection. This allowed people to maintain their distance and avoid entering the areas where people are crowded. However, job duties or social contact is sometimes difficult to avoid being in the public areas. Contactless or touchless society then shifted into account. The focus is on adopting technology and practices that allow social and economic activities to continue while minimizing the risk of disease transmission through physical contact. This can include contactless payment systems, virtual meetings, facial recognition technology, and the use of robots for tasks that would normally require human contact. The goal is to reduce the spread of disease while maintaining as much normalcy and efficiency as possible in daily life.

The contactless approach to internet of thing and wearable medical technology emphasizes the need for comfort and ease of use, while also respecting privacy and avoiding interference with daily activities. Following the contactless approach, we aim to create systems that can provide medical monitoring and care without the need for invasive or uncomfortable devices, through the use of contactless technology such as sensors and platforms. These systems include health monitoring, elderly care, and medicine identification, which are designed to provide medical personnel with the information they need to ensure the well-being of their patients.

4.1. Indoor Camera-Based System for Human Physical Distance Tracking

The proposed method for determining physical distance in indoor environments introduces the use of end-to-end cameras to track a person's position, movement direction, and seat activity. The system does not identify individuals, but instead records their location for the purpose of monitoring physical distancing. The research mainly focuses on two main aspects: detecting a person's location and detecting seat positions [7].

4.1.1. Seat Detection

The seat detection in the proposed system uses contour color extraction [8] on the top part of the seat or table. It extracts unique contour shape as a feature, as shown in Figure 1. The results indicate that contour detection works well for the first rows of seats, but may have difficulties detecting seats in the rest of the rows.

The perspective transformation [9], [10] has been applied to changes the original image projection into a new visual plane for system requirements using Equation (1).

$$[x', y', w'] = [u, v, w] \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (1)$$

For improving the seat detection ability, we apply the perspective transformation with the selection of the top seat area in the room as the region of interest (ROI), before seat contour detection. The process allows the system to accurately detect the seats in the room.

4.1.2. Person Detection

The proposed system detects a person in the specified area using YOLOv3 algorithm, which uses trained weights and data sets to detect objects. The pre-trained model and function selected specifically for human body detection were utilized in the algorithm. as illustrated in Figure 3.

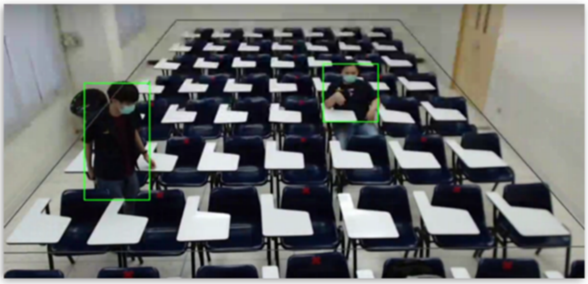

Figure 3. Human body detected using YOLOv3 in green boxes, and the image reference frame in black line.

In the standard pre-trained YOLOv3 [11],[12], the bottom center of the detection box is used as the reference point for a person's location. The proposed system improves person location reference point by first calculating the height-to-width ratio of the detected human object and rounding it, which better appropriate for the indoor environment being monitored. The ratio is denoted as $Q_{Box} = h_{Box}/w_{Box}$. Where h_{Box} and w_{Box} represent the height and the width of the box, respectively.

The classification of standing and sitting is based on the ratio of QBox, which is calculated as the height of the box (hBox) divided by its width (wBox) ($Q_{Box} = h_{Box}/w_{Box}$). And it can be concluded that

- if the value of Q_{Box} >= (greater than or equal) 1.6, refers to a standing person in the box
- if the value of Q_{Box} < 1.6, refers to a sitting person in the box

$$c = \begin{cases} 0.775; & \text{if } Q_{\text{Box}} \geq 1.6 \\ 0.675; & \text{otherwise} \end{cases} \quad (2)$$

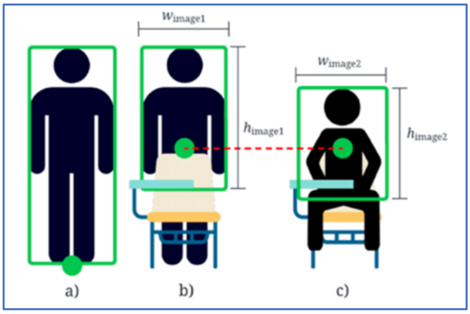

Figure 4. Illustration of human body detection reference point (green). (a) original approach (at the bottom-middle point of the green box), (b) a person standing between seats (77.5% of vertical proportion from the top-middle point as $h_{\text{image}_1}/w_{\text{image}_1} \geq 1.6$), (c) a person sitting on the seat (67.5% of vertical proportion from the top-middle point as $h_{\text{image}_2}/w_{\text{image}_2} < 1.6$).

The distinction between standing and sitting scenarios is illustrated in Figure 4 (b) and 4 (c) compared to Figure 4 (a) which shows the conventional algorithm for determining the reference location of a person. Here, the location of the person in each frame is identified using a modified algorithm. The conventional point at the bottom-middle of the detected human body has been replaced with a reference point c, which can take the values 0.775 or 0.675 for a standing or sitting person, respectively. The reference points for standing and sitting cases are calculated using Equation (2) and this approach was used to improve the accuracy of location of persons in a room environment.

4.1.3. Physical Coordinate Calculation

The reference point coordinates for seats and persons were determined and used to calculate physical coordinates by converting the image coordinates to physical coordinates using two reference parameters from the room's physical dimensions, including the real size of the room and the pixel size of the region of interest in the image frame. The ratio between image and room size was calculated using Equation (3).

$$Q_{\text{Physical}} = \frac{ImageSize}{RoomSize} \quad (3)$$

4.1.4. Performance Evaluation and Discussion

The proposed system uses seat contour detection to initiate seat positioning in a room. Nonetheless, the accuracy of the detection decreases in the back rows according to constraints from further seats. To improve the detection ability for the back row seats, a perspective transformation is proposed. This transformation increases the ability of the seat detection algorithm to detect seats in the back rows.

For physical distancing monitoring, the system uses the upper left-hand corner of the seat boundary area after the perspective transformation as the reference point. This point is used to transform the image space into a bird-eye view, allowing for calculation of physical locations of seats and people [13]. While the system can estimate actual distances in real-world units, there may still be errors from the transformation, which have been studied in various related researches [14], [15], [16]. To improve the accuracy of image-based distance measurement, we need to select the proper area of interest and algorithm to calibrate the image-physical distance.

A camera-based system was implemented to determine the physical locations of seats and people in a room. The average error of seat location determined by the system was ±5.25 cm. with a standard deviation of 4.64 cm. The small error suggests the overall performance of the system in determining real-world locations. The system can accurately determine whether people are at an appropriate physical distance (180 cm.) apart from others for COVID-19 prevention, and the uncertainty of 5.25±4.64 cm. has a small effect on the scale of distancing. The system is reliable in providing proper physical distancing suggestions.

To classify whether a person is sitting or standing, we used the height-to-width ratio of the area surrounding a detected person as the criteria. Based on this classification, an appropriate reference point was determined to represent the spatial location of the person in the room space. The maximum boundary for a person sitting on a seat was found to be 46x87 cm., which is reasonable according to seat dimensions. The system is able to accurately determine whether a seat is occupied or available This method solved the problem of the hidden part of the human body behind the seat, allowing for more precise location identification. The improvement of the body reference point shows the potential for developing a more precise location identification system in the future. Figure 5 illustrates the system workflow of the camera-based indoor physical distancing log recording system.

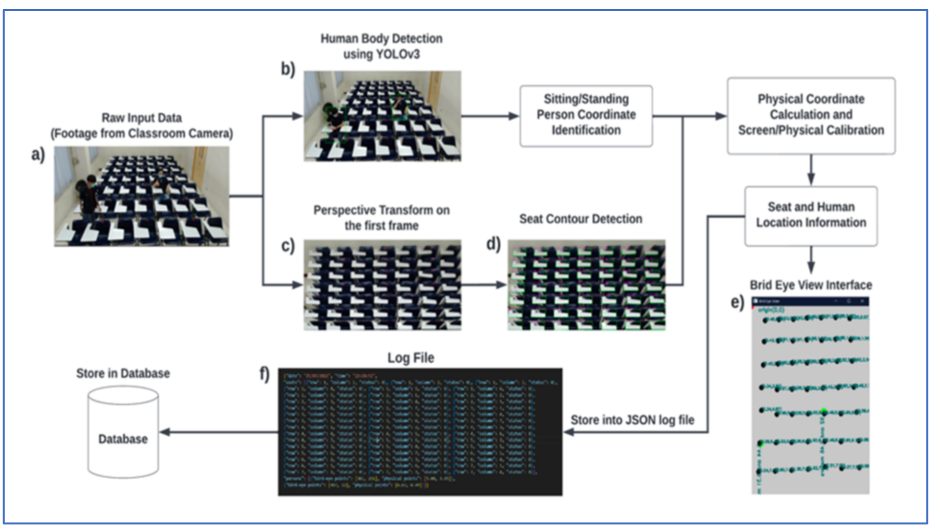

Figure 5. The system workflow for camera-based indoor physical distancing log recording system.

4.2. Smart Street Light Monitoring and Visualization Platform

Smart lighting is a concept that utilizes artificial intelligence (AI) and the Internet of Things (IoT) technology to manage and control lighting systems in cities. The implementation of smart lighting has become a popular trend in modern cities as it enables efficient and effective management of lighting equipment, reduces energy consumption and costs, and enhances the overall safety and security of the city. Smart lighting has been implemented in many major cities worldwide as an important solution for smart city management. The ability to monitor and control lighting equipment in real-time, collect and analyze data from devices and sensors, and the ease of use of the platform make it a convenient solution for managing and improving the lighting systems in cities.

The Smart Lighting project at Thammasat University, Rangsit Campus, is an example of the implementation of this concept. The project involves the development of a web application on a cloud platform that serves as a central control system for monitoring, controlling, and collecting data from lighting equipment and sensors in the university campus in real-time. The platform provides a user-friendly interface for monitoring and controlling the lighting equipment, and it also visualizes the data collected from the devices and sensors in the area, making it easier for users to analyze and understand the information, and for the efficient maintenance by campus staff as well. The platform, moreover, this platform aims to improve energy efficiency and align with Thammasat University's sustainable development goals through monitoring and data analysis for optimal energy consumption [17].

For the first phase, the 167 smart light poles, equipped with LED lamps and adjustable dimming levels were installed. The pole-to-pole separation of approximately 20 meters ensures optimal coverage with the general regulation of street light in Thailand and provides a more efficient and effective lighting solution.

4.2.1. Smart Street Light Installation

In collaboration with the Minebea Mitsumi Inc., of Japan, smart street lights and environmental sensors are installed in six zones on five roads within the Rangsit campus. The project equipment consists of 167 controllable lighting devices with brightness sensors attached to each lighting device, environment station including weather condition and light sensors, three gateways for connecting all equipment to an external control system.

As depicted in Figure 6, the smart LED lights and their associated illuminance sensor are connected to the control node and CMS Neptune SC-v6.0.3 platform operated by the manufacturer (Paradox Engineering, Switzerland). The API can be accessed via REST (the Representa- tional State Transfer) over HTTP (Hypertext Transfer Protocol) to collect data and control the local device. The backend of the system must be able to send HTTP requests and receive responses from the CMS API. The front-end visualization is presented as a web application, which also connected to the lighting system via the CMS API, accessible from any devices with a web browser, and can display received data and device status. Advantageously, the web application can be accessed from anywhere at any time.

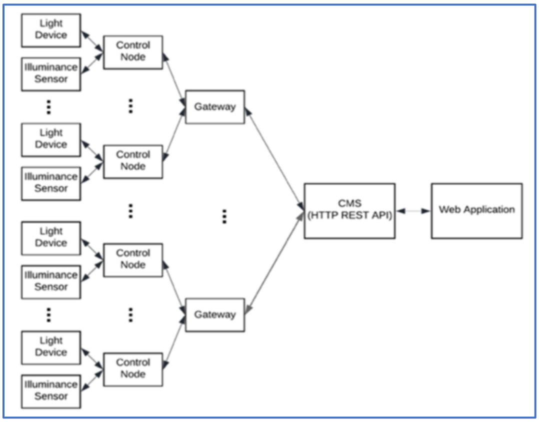

Figure 6. Device connection in the platform.

4.2.2. Development of Back-end and Front-end System

To develop the web application, it is necessary to establish both the back-end or the server-side and the front-end or the client side of the application. Node.js, a JavaScript runtime environment, is used in web application development as it allows JavaScript to run on both ends. [18]. On top of node.js, the Express.js web framework module is introduced because of its highly configurable nature, thus allowing for more customization on the web application development [19].

Express.js provides a robust and convenient routing system that allows developers to create custom API endpoints to handle HTTP requests and send responses. The Axios module [20] makes it easy to send HTTP requests and receive responses, which is useful when connecting to third-party APIs like the CMS API. For security, it's common to implement authentication and authorization mechanisms to protect the API and its resources. The use of cookies to store user tokens can help to improve the performance of the authentication process by reducing the number of requests to the CMS server. By using these technologies, developers can create a back-end application that integrates with the CMS API and provides a secure and efficient way for users to access and control devices through the CMS. The back-end application communicates with the CMS API to retrieve data from lighting devices and environmental sensors. It processes and reformats the data received from the API and sends it as an HTTP response in JSON format to the front-end application, making it easier to display and use. The API also provides additional information, such as device information and status, to support the monitoring system on the front-end. The process in the back-end application is illustrated in the provided Figure 7.

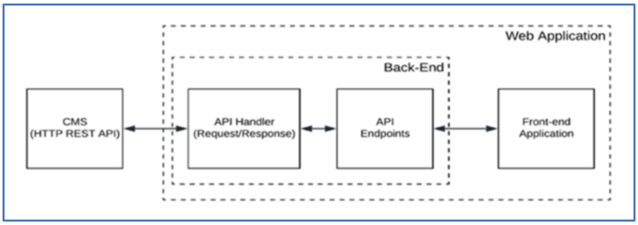

Figure 7. The connection between CMS API and the back-end processing of the web application.

The front-end web application is designed to be user-friendly and accessible via the internet or cellular network using HTTP protocol. To ensure that the web application behaves the same across all devices, including mobile and desktop devices, responsive web application design with Bootstrap is implemented. This allows for fast and optimized rendering of web pages on devices with different screen sizes, improving the user experience on mobile devices.

Figure 8. The dashboard interface used in the web application.

Chart.js, an open source JavaScript library [21], is used for data visualization on the dashboard. The library provides a wide range of customization options and is used in the web application to display data from environmental sensors including temperature and humidity from the past 2 hours, in the form of line graphs. The numerical data of illuminance, Ultra Violet A and B indices, wind velocity, wind direction, and air pressure are updated every 10 minutes. The dashboard interface is displayed in Figure 8.

Finally, the device location is displayed on an interactive map using Leaflet.js [22]. The interactive map provides real-time information on the device information and precise location. The web application, a combination of front-end and back-end development, s deployed on Microsoft Azure App Service [23], which supports Node.js applications and has a streamlined deployment process. After deployment, a public URL is available for accessing the web application to monitor the smart lighting system and retrieve data from environmental sensors.

4.2.3. Illumination Data Analytics and Prediction Models

Figure 9 illustrates the results of the first set of analyses, which focuses on examining the hourly average illuminance values over a period of nine months (February to October 2022). It was observed that the natural light illuminance in Thailand exhibited a predictable pattern of increasing from 06:00, peaking during midday, and declining to zero at approximately 18:00. Additionally, a correlation matrix was analyzed, as shown in Figure 10, to assess the relationship between the selected dataset features. The results indicated that Ultraviolet A and Ultraviolet B were highly correlated with illuminance values.

Figure 9. The hourly average of illuminance values over the period of nine months, covering February to October 2022.

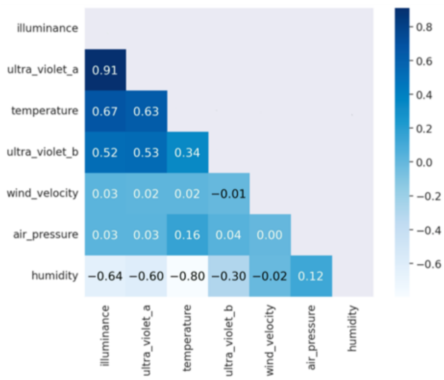

Figure 10. Investigation of the strong positive correlation between Ultraviolet A and illuminance values by generating a correlation matrix for every pair of variables.

Machine learning algorithms were implemented to forecast future illuminance timestamps in this study. The correlation matrix showed a significant correlation between Ultraviolet A and Ultraviolet B with illuminance values; therefore, they were eliminated from the dataset to prevent overfitting. Five environmental parameters, namely humidity, temperature, air pressure, illuminance, and wind velocity, were retained as input parameters. Date and time were also included as parameters during training. The performance of each model was assessed using a correlation coefficient metric by comparing the predicted values with the actual values. Table 1 presents the results of experiment, which compared the performance of four different machine learning models, including Gradient Boosting, XGBoost, Random Forest, and Decision Tree, across different analysis window sizes (3, 4, 5, 6, and 7 days) for predicting illuminance values in the environmental dataset.

Table 1. Evaluation of correlation coefficient between predicted and actual illuminance values on test data using varied machine learning models and window sizes.

Window size / Models	3 Days	4 Days	5 Days	6 Days	7 Days
Gradient Boosting	0.918	0.914	0.919	0.912	0.912
XGBoost	**0.922**	**0.920**	**0.920**	**0.919**	**0.903**
Random Forest	0.919	0.917	0.918	0.915	0.918
Decision Tree	0.839	0.840	0.848	0.838	0.840

Typically, a model is deemed better if it has a higher correlation coefficient between predicted and actual values. According to the results in Table 1, the optimal machine learning model varied based on the size of the analysis window. For a 3-day window size, the XGBoost model had the highest correlation coefficient of 0.922, making it the best-performing model among the selected ones.

5. Conclusion

The Thammasat AI City platform stands as a visionary solution for advancing urban management through the integration of cross-domain data connectivity and machine learning, enabling comprehensive data collection. Within this study, we have validated the platform's effectiveness in two vital domains: the monitoring of street lights and the tracking of indoor human physical distance. The street light monitoring system empowers real-time insights into lighting status, energy consumption, and maintenance requirements, thereby optimizing energy efficiency and cost reduction. Simultaneously, the camera-based indoor system ensures social distancing adherence for public safety. As we look to the future, potential avenues for further exploration could involve expanding the platform's applications to encompass additional urban challenges, optimizing data analysis techniques, and fine-tuning the integration of AI-driven insights for more precise decision-making. Ultimately, the Thammasat AI City platform remains dedicated to enhancing the quality of urban life while aligning seamlessly with the principles of sustainable urban development.

Acknowledgement

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