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A Novel Digital Twin Framework for Adaptive Urban Weather Visualization Using IoT and Fuzzy Logic

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Abstract: This research identifies the urgent need for adaptive and real-time urban weather visualization models to support city planning and decision-making. The proposed solution involves the use of digital twin technology integrated with the Fuzzy Sugeno method to handle dynamic and complex environmental data. The novelty of this approach lies in its ability to provide real-time, adaptive visualizations through a combination of IoT (Internet of Things) data and advanced fuzzy logic processing, enhancing the accuracy and relevance of urban weather monitoring. This method enables the system to process real-time weather data collected from IoT sensors distributed throughout the city, resulting in accurate and relevant visualizations. The weather data, including temperature, humidity, and wind speed, is sent to a data centre where the Fuzzy Sugeno method is used to transform this data into visualizable weather information. The weather visualizations include conditions such as heavy rain, regular rain, drizzle, overcast, cloudy, sunny cloudy, somewhat cloudy, and sunny. The results of this study demonstrate that the system can display weather conditions adaptively and in real-time, significantly contributing to the understanding and management of urban heat islands. In ten experiments with temperature ranges from 21°C to 34°C, humidity from 55% to 87%, and wind speeds from 12 km/h to 32 km/h, the dominant defuzzification value was 0.6, corresponding to sunny cloudy weather conditions. The implementation of this system also shows improvements in the quality and accuracy of weather information presented, thereby aiding in more responsive and sustainable urban planning.

Keywords: Digital twin, Fuzzy Sugeno, Weather visualization, IoT, Sensors.

1. Introduction

In the era of increasingly rapid urbanization, visualization of the urban environment plays an important role in supporting urban planning and decision-making. Visualization technology allows planners and decision-makers to model city data comprehensively so they can more effectively understand the dynamics of the urban environment [1]. However, the biggest challenge in urban visualization is ensuring that the visualization model can adapt in real-time to dynamic, changing environmental conditions.

The main problem in urban environmental management is the need to display information on weather conditions that can change adaptively. Adaptive visualization allows the system to adjust the display based on environmental data received in real time, such as temperature, humidity, and wind speed [2]. This need is increasingly urgent considering the challenges faced in mitigating the impacts of urban heat islands and climate change [3, 4]. Implementing real-time data visualization on a smart city platform can increase efficiency and responsiveness in overcoming urban environmental problems [5].

Several previous studies have shown the importance of digital twin technology in providing accurate digital representations of the physical environmental conditions of cities. This technology enables real-time simulation and analysis, which is very important in dealing with phenomena such as urban heat islands [6]. Nevertheless, several studies still show limitations in real-time data integration and adaptive capabilities of visualization systems. For example, research by Brazauskas et al. emphasized the challenges in spatiotemporal data representation and novel visualization in smart environments [5]. Additionally, Ji et al. identified the need for a visual IoT architecture that can improve the end-to-end performance of next-generation smart cities [7]. Analysis of these studies suggests gaps in terms of real-time visualization adaptation that can be addressed by the development of more sophisticated and integrative methods such as those proposed in this study.

An approach is needed that is able to deal with the uncertainty and complexity of environmental data to achieve effective adaptive visualization. One approach that can be used is through the integration of digital twin technology with flexible and responsive data analysis methods. Digital twin technology allows real-time simulation of urban environmental conditions but requires additional methods to interpret and display dynamic data accurately. In this context, the use of methods that are able to handle data uncertainty and provide interpretive results becomes very important. This method must be able to manage and process data from various IoT sensors spread across the city to ensure accurate and up-to-date visualization. Thus, methods such as Fuzzy Sugeno can provide the right solution to meet these needs, considering their advantages in handling uncertain data and producing flexible and adaptive decisions. This method allows the system to adjust the display based on real-time data received, resulting in a more accurate and relevant visualization of weather conditions. This method is also very effective in managing dynamic and complex environmental data and can produce more accurate decisions for the visualization of weather conditions [8].

In this research, weather condition data is obtained through IoT sensors spread throughout the city. These sensors send data in real-time to a data centre, which is then used to update the digital twin model and produce accurate and up-to-date visualizations. This IoT integration improves visualization accuracy and enables rapid response to changing environmental conditions [9,10]. In addition, the use of crowdsensing methods can speed up data collection and reduce operational costs, thereby increasing the efficiency of urban monitoring systems [11].

This research aims to develop a visualization system capable of displaying changes in urban weather conditions adaptively and in real-time based on data obtained from IoT sensors. Through the application of digital twin technology and the fuzzy Sugeno method, this research is expected to make a significant contribution to the understanding and management of urban heat islands. The use of VR (Virtual Reality) and big data in smart city visualization can help improve user interaction and understanding of complex data [12-14].

The main contributions of this research include the development of an integrative model that allows a better understanding of the dynamics of urban heat islands and the practical application of adaptive visualization technology in urban planning and management. The results of this research not only fill the shortcomings of previous studies but also provide innovation in the application of technology for more responsive and sustainable urban environmental management [15]. Thus, the approach proposed in this research offers a comprehensive solution that city stakeholders can adopt to plan and manage the dynamics of the urban environment more effectively and efficiently. This innovation is expected to provide direct benefits in efforts to mitigate the impact of urban heat islands and improve the quality of life in urban cities [16].

The organization of this paper is structured to comprehensively address the challenges and solutions in urban weather visualization. The Introduction provides the background of the problem and outlines the proposed solution, emphasizing the integration of digital twin technology with the Fuzzy Sugeno method. The Related Work section reviews existing literature to highlight the gaps and the necessity for real-time adaptive visualization systems. The Design and Method section details the IoT design, the methodology for weather determination using the Fuzzy Sugeno method, and the framework for weather visualization. The Results and Discussion section presents the data retrieval process using IoT, the outcomes of weather determination, urban visualization results, and a comparison study to evaluate the system’s effectiveness. Finally, the Conclusion summarizes the key findings and discusses future research prospects.

2. Related work

A number of previous studies have explored the application of digital twins in visualizing urban weather conditions using IoT data. Lee, Kim, and Jang [17] developed a platform that detects, reconstructs, and visualizes dynamic data moving in digital twin cities. The platform enables visualization of city conditions in motion with 3D data, providing an in-depth view of the road situation and weather conditions at any given time. However, this platform is limited by its focus on static 3D data visualization and lacks adaptive capabilities to respond to real-time changes in environmental conditions. Haidukevych and Doroshenko [18] investigated the application of digital twins for weather forecasting on mobile platforms, emphasizing the importance of real-time access to air quality information and weather forecasts for different areas of the city, which is especially important considering the increasing environmental problems. This research shows the need for better technology integration to support adaptive real-time data visualization.

Other research highlights the importance of large-scale visualization and supercomputing for digital twins of cities. Holiman et al. [19] developed a cloud computing software architecture for 3D pixel visualization of urban IoT data supporting daily updates. They show that GPU computing resources in the cloud can be used to generate therapeutic pixel visualizations in less than an hour. Despite its computational efficiency, this approach primarily focuses on static pixel visualization without adaptive real-time updating capabilities. Dembski et al. [20] presented an urban digital twin prototype for the city of Herrenberg, Germany, which includes a 3D model of the built environment, urban mobility simulation, and wind flow simulation. This prototype is used in a public participatory process to assist democratic urban planning. Although this prototype is valuable for public participation, it lacks a robust mechanism for integrating real-time environmental data, limiting its effectiveness in dynamic urban weather visualization.

In addition, research conducted by Kikuchi, Fukuda, and Yabuki [21] developed a city digital twin approach for the visualization of flooded cities using the integration of augmented reality and drones. The system allows visualization of city conditions from a bird's eye and user's perspective, assisting in flood risk management in urban spaces. While this system provides a novel perspective on flood risk, it does not offer a comprehensive solution for continuous real-time environmental data integration and adaptive visualization. They also developed a method that combines AR (Augmented Reality) and 3D models to overcome the occlusion problem, providing a more comprehensive and realistic view of urban conditions from multiple perspectives [22]. Meanwhile, research by Lee et al. [23] focused on developing a Unity3D-based geospatial platform to manage individual mobility data in an urban digital twin, enabling real-time visualization of vehicle and pedestrian mobility data. This platform integrates data from public CCTV and enables long-term storage and management of vehicle route information while maintaining privacy through the anonymization of number plates. However, this platform is primarily geared towards mobility data visualization and does not fully address the complexities of real-time adaptive weather visualization.

Research by Somanath et al. [24] developed a semi-automated workflow that includes procedural context generation using Unreal Engine and integration of various types of urban analysis data for visualization. They highlight the importance of large-scale visualization and analysis of complex urban data for better city planning. This workflow, though effective for urban analysis, does not incorporate mechanisms for real-time adaptive visualization based on continuous IoT sensor data. Research by White et al. [25] also emphasizes the importance of public participation in urban planning through the use of digital twins that enable citizen interaction with 3D city models in real time. This study shows that by publishing city models online, citizens can provide direct feedback on planned changes in urban policy and design. These studies show the importance of technology integration for real-time and adaptive visualization of urban conditions. However, most studies still focus on visualization and simulation aspects without deeply addressing the challenges of integrating dynamic and complex environmental data from multiple IoT sensors. Despite its benefits for public engagement, this approach lacks the capability to integrate and adapt to real-time environmental data dynamically.

These studies show the importance of technology integration for real-time and adaptive visualization of urban conditions. However, most studies still focus on visualization and simulation aspects without deeply addressing the challenges of integrating dynamic and complex environmental data from multiple IoT sensors.

An effective approach is needed to achieve adaptive visualization that can manage the uncertainty and complexity of environmental data. One viable strategy involves integrating digital twin technology with flexible and responsive data analysis methods. Digital twin technology enables real-time simulation of urban environmental conditions but requires supplementary methods to interpret and display dynamic data accurately. Fuzzy logic methods present an optimal solution to address this

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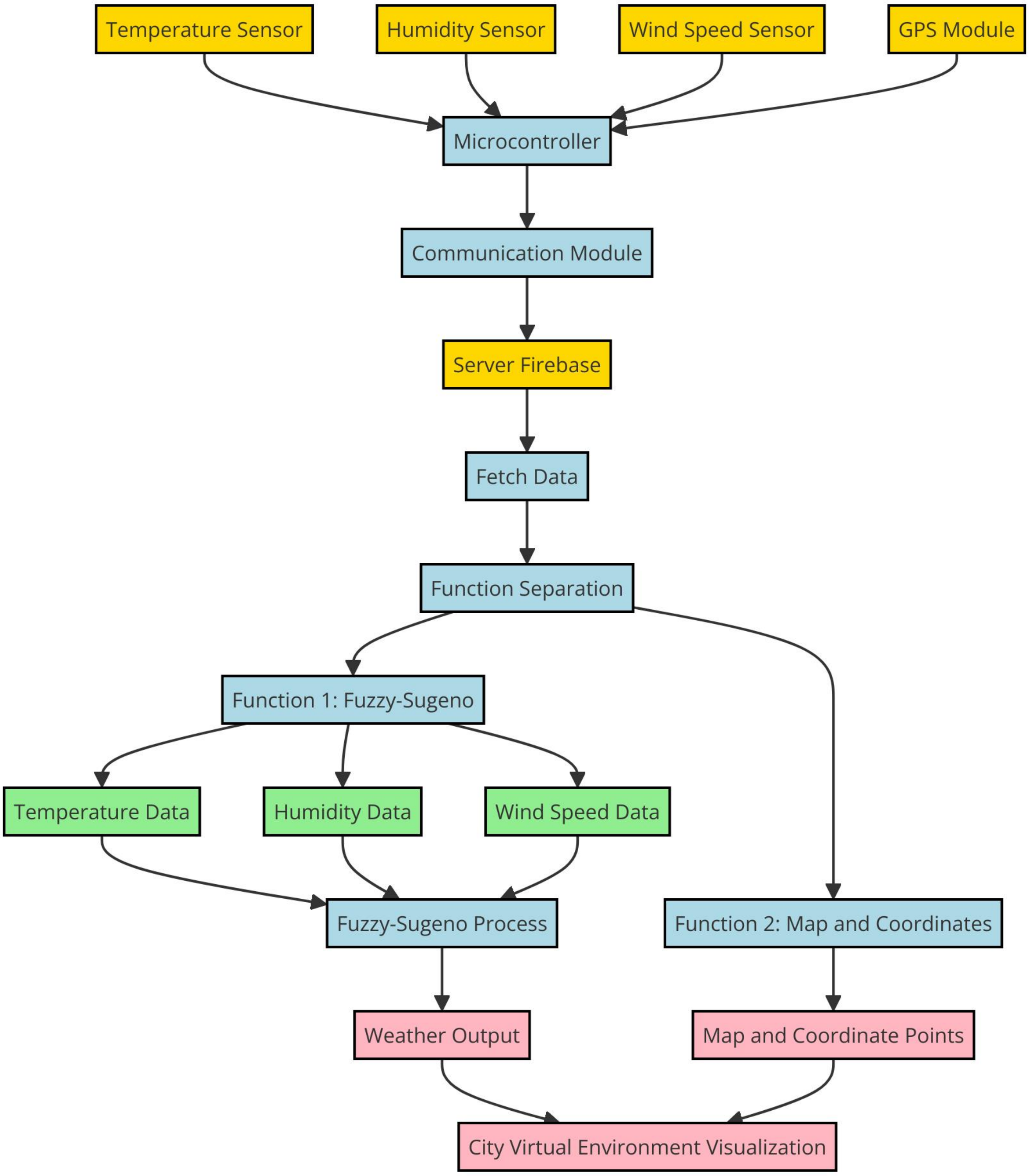

Figure. 1 Proposed system

need. These methods are proficient in handling uncertain data and making flexible, adaptive decisions, which is crucial for visualizing ever-changing weather conditions. Specifically, the Fuzzy Sugeno Method offers a superior solution for managing data uncertainty, resulting in more accurate and relevant weather visualizations based on real-time data from IoT sensors. Integrating this method with a digital twin platform is anticipated to yield visualizations that are more responsive to environmental changes, thereby enhancing the quality and accuracy of the information presented.

3. Design and method

This research aims to develop adaptive visualization of urban weather conditions using IoT and Digital Twin technology. The method used involves collecting data from various environmental sensors, processing the data using the Fuzzy Sugeno method, and visualizing the data in the form of an interactive virtual environment. Fig. 1 shows the system design proposed in this research.

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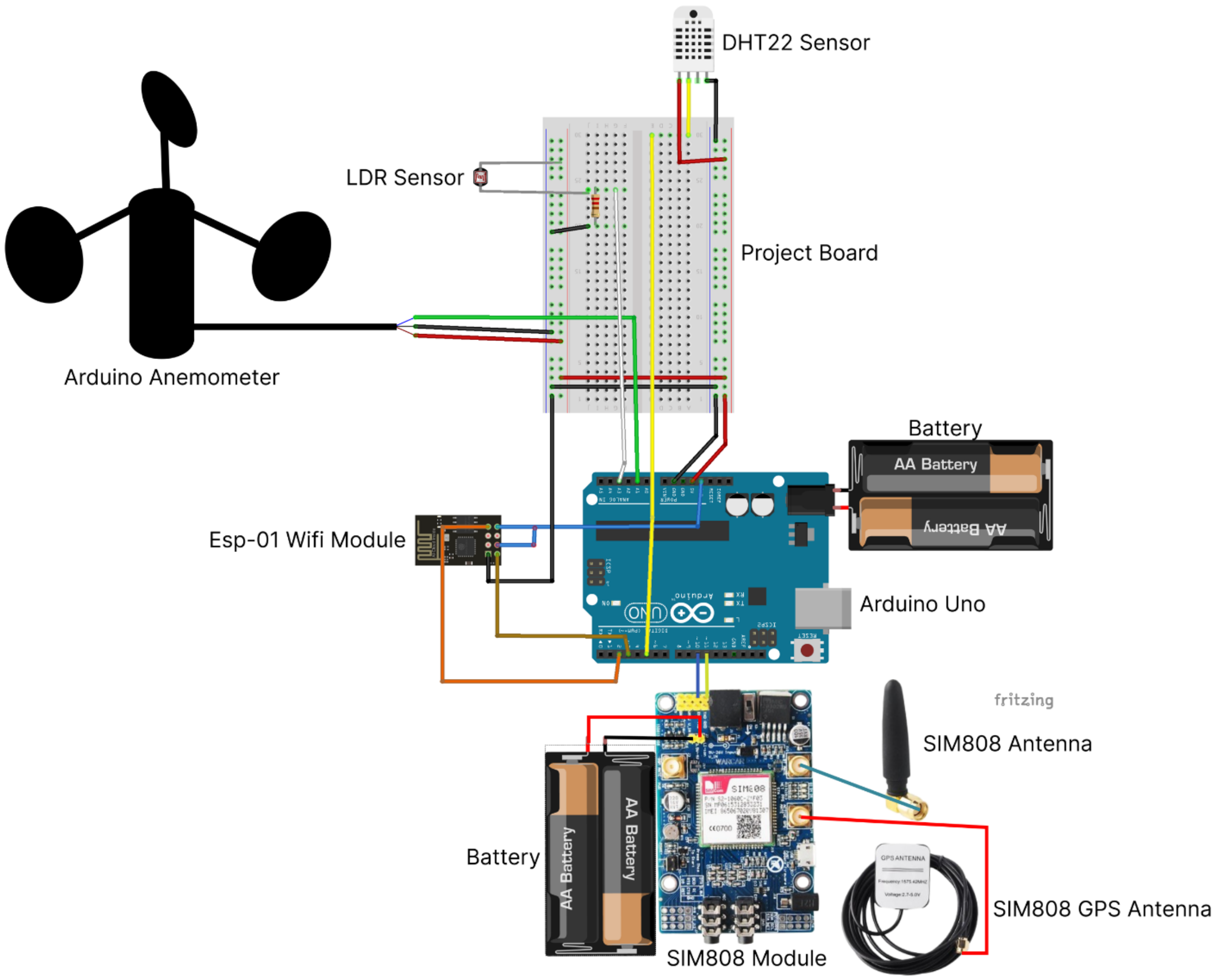

Figure. 2 Design of IoT circuit

3.1 IoT design

Based on Fig. 1, input data is obtained from an IoT system that consists of several types of sensors, including temperature, humidity, wind speed, and position sensors via GPS. The temperature and humidity sensor used is the DHT22 type. This temperature and humidity sensor has an NTC (Negative Temperature Coefficient) type thermistor whose resistance value is inversely proportional to the increase in temperature. This temperature and humidity sensor has an output in the form of a digital signal. The output value of this sensor changes based on the rise and fall of the thermistor resistance, which affects the rise or fall of the temperature.

Apart from that, in this research, we used a wind speed sensor of the JL-FS2 type. This sensor has an output in the form of current. Therefore, a current-to-voltage converter is needed so that the Arduino Uno can easily read it. When the wind speed sensor receives wind, the sensor will produce current. The stronger the wind detected by the sensor, the greater the resulting current output. The current produced by the sensor will then enter the converter to be converted into voltage. The output from the converter in the form of voltage will then be sent to Arduino.

These sensors are connected to an Arduino Uno microcontroller, which functions to collect and store data. After the data is collected, the microcontroller will send the data to the server via the WiFi connection available on the ESP-01 module. The SIM808 module is used to obtain GPS data, which helps in determining the location of the device [26]. The IoT system used in this research is shown in Fig. 2. The data that the Arduino Uno has collected is then sent to the Firebase server via the ESP-01 module. Firebase is used as a server to store data in real time, allowing fast and easy access to the data needed for further analysis [27].

3.2 Weather determination using fuzzy

Once the data is collected on the Firebase server, it is divided into two main functions.

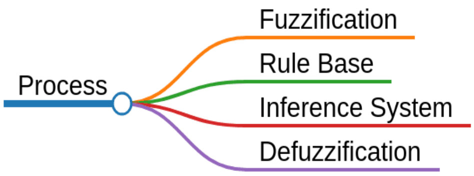

Figure. 3 Fuzzy process

The first function is to run the Fuzzy Sugeno method with three inputs and one output. The three inputs are temperature in the range 0-30°C, humidity in the range 60-100%, and wind speed in the range 0-30 km/hour. The resulting output is the weather conditions produced through the defuzzification process [28]. This process involves several steps, starting from fuzzification of input data, application of fuzzy rules, defuzzification to obtain final results, to evaluation of results, as shown in Fig. 3. The defuzzification results are then displayed in the form of a weather environment that matches the data taken from the Firebase server. The second function is to obtain coordinate data from the location of the detection device. This coordinate data is used to display the map and device location points on the map. This technique allows visualization of the position of the detection device in the context of the wider city environment.

Fuzzification is the process of changing input crisp values into a fuzzy set by determining the degree of membership of each value in the fuzzy set. In this research, to determine a location's weather conditions, several inputs are needed that reflect those conditions. The inputs used are temperature, humidity and wind speed, as implemented by the Meteorology, Climatology and Geophysics Agency (BMKG). These three inputs are fuzzyified into fuzzy sets of temperature, humidity and air speed [29,30].

In the first stage of fuzzification, temperature is one of the main parameters analyzed. The temperature membership function has a range from 0°C to 40°C. Triangular curves are used to describe temperature variables, where the “cold” variable ranges from 0°C to 10°C, the “warm” variable ranges from 5°C to 30°C, and the “hot” variable ranges from 25 °C to 40°C. The degree of membership of each temperature variable is calculated using an increasing or decreasing linear membership function formula. The basic formula for the linear membership function increasing $\mu\ li\ (x)$ and decreasing$\mu\ ld\ (x)$y used in this study is shown in Eqs. (1) and (2).

$$\mu\ li\ (x) = \begin{cases} 0 & if\ x \leq a \\ \frac{x-a}{b-a} & if\ a < x \leq b \\ 1 & if\ x > b \end{cases} \qquad (1)$$

$$\mu\ ld\ (x) = \begin{cases} 0 & if\ x \leq a \\ \frac{b-a}{b-a} & if\ a < x \leq b \\ 1 & if\ x > b \end{cases} \qquad (2)$$

These formulas work by dividing the membership interval into several parts, where each part indicates a different degree of membership. For an increasing linear function, membership starts from 0 at point a and increases linearly until it reaches 1 at point b. In contrast, for a descending linear function, membership starts from 1 at point a and decreases linearly until it reaches 0 at point b.

Using this basic formula, we can determine the degree of membership of each input based on its position in a predetermined interval, making fuzzy inference possible in the next step.

A similar process is also applied to humidity, which is the second input in this fuzzy model. The humidity membership function has a range from 0% to 100%. Each triangular curve describes certain conditions, where the “dry” variable ranges from 0% to 30%, the “moist” variable ranges from 20% to 70%, and the “wet” variable ranges from 60% to 100%. The degree of membership of each humidity variable is also calculated using an increasing or decreasing linear membership function formula. With the same approach, membership increases from 0 to 1 as humidity increases within a specified interval or decreases from 1 to 0 as humidity decreases.

Apart from that, the wind speed is also fuzzified using the same approach. The airspeed membership function has a range from 0 km/h to 40 km/h. Each triangular curve describes certain conditions, where the “slow” variable ranges from 0 km/h to 10 km/h, the “normal” variable ranges from 5 km/h to 30 km/h, and the “fast” variable ranges from 25 km /hour up to 40 km/hour. The degree of membership of each airspeed variable is calculated using the increasing or decreasing linear membership function formula. With the same formula, membership is calculated based on a given wind speed and the corresponding interval.

After determining the degree of membership for each input, the next step is to build a rule base for inference. The rule base used in this research consists of 27 rules. Each rule describes a specific weather condition based on a combination of temperature, humidity, and wind speed inputs.

The inference process then combines all the rules based on the available data. In this research, the min implication function is used, where the three membership function conditions must be combined to produce weather output. The min implication function is used because to get the membership value of a weather condition, we have to take the minimum value of the membership degree of each input (temperature, humidity, and wind speed). The minimum implication formula used in this research is shown through Eq. (3).

$$\mu(s \cap k \cap g) = min(\mu_s[x], \mu_k[x], \mu_g[x]) \quad (3)$$

In the context of this research, the variables s, k, and g represent the membership degrees of temperature, humidity, and wind speed. The result of this min operation is the degree of weather output membership that is in accordance with the rules used. The weather output includes heavy rain, regular rain, drizzle, overcast, cloudy, sunny cloudy, somewhat cloudy, and sunny.

The final process in fuzzy design is defuzzification, which combines all fuzzy outputs into specific results that can be used for system output. In the fuzzy-Sugeno method, the results of fuzzy inference are constant values. This method is different from the Mamdani method, which produces output in the form of a fuzzy set. For example, an input temperature of 22.3°C, humidity of 89%, and wind speed of 33.2312 km/h produce a weather output of “Sunny Cloudy” with a value of 0.7. This process produces output that can be used to predict weather conditions based on temperature, humidity and wind speed data obtained from the location under study.

3.2 Weather visualization design

Prediction data is used as a basis for visualizing weather conditions in the city environment. This research takes the location of Malang City as its theme, which consists of five sub-districts with their unique environments.

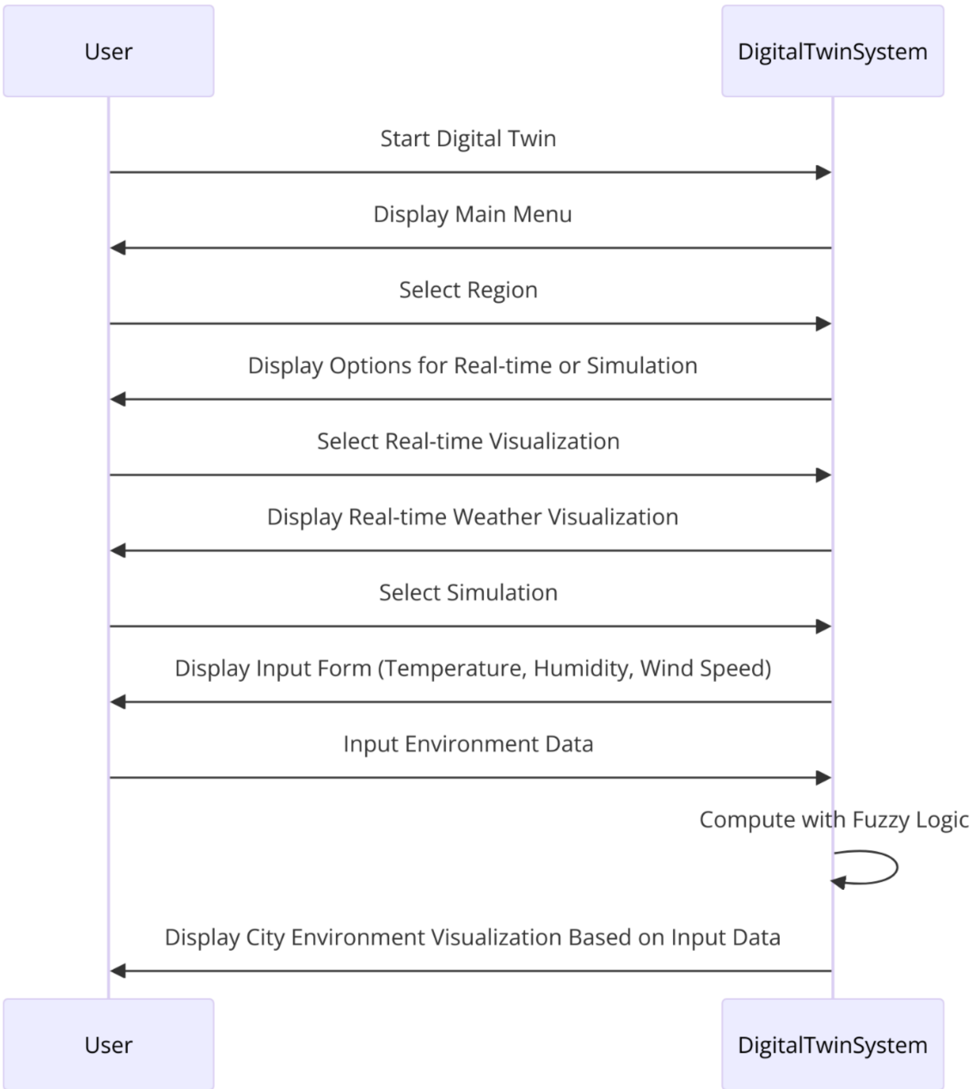

Figure. 4 User interaction model with digital twin system

Malang was chosen because it is located in the highlands and has a tropical climate, providing microclimatic diversity, which is important for validating weather prediction models. The diversity of topography and climatic conditions in Malang makes it an ideal subject for studies on how altitude influences weather patterns. In addition, the accessibility and availability of historical data from BMKG supports the selection of Malang as the location for this research.

By considering these factors, user interaction design in a virtual digital twin environment will play an important role in visualizing and understanding weather conditions in Malang. The user interaction model with the digital twin system proposed in this research is shown in Fig. 4. Interaction design for a weather visualization system in a digital twin environment begins when the user activates the digital twin system. Once activated, the system displays a main menu that allows users to select the specific area in Malang City that they want to simulate. This selection of regions is important because it adapts the simulation to the unique climatic and geographic characteristics of the selected area, thereby providing a more accurate and relevant visualization. Users are then given two options: real-time weather visualization or simulation based on predefined data.

When the user selects real-time visualization, the system immediately retrieves and displays current weather conditions, including temperature, humidity and wind speed in the selected region. This real-time data comes from reliable sensors and weather stations, ensuring that the conditions displayed are always up-to-date and accurate. This feature is very useful for monitoring and decision-making in real-time scenarios, such as urban planning and emergency response.

Conversely, if users select the simulation option, they can enter specific environmental data to simulate weather conditions. The system will display an input form where the user can enter temperature, humidity and wind speed data. Once the data is entered, the system uses fuzzy logic to calculate and simulate weather conditions based on the input. The calculated data is then visualized, allowing users to see a detailed representation of the city environment under predefined conditions. This interaction design not only provides flexibility in visualizing real-time and simulated weather conditions but also leverages the power of fuzzy logic to offer a more immersive and adaptive simulation experience.

4. Result and discussion

In this section, we present comprehensive findings from our research, which includes several important components: Data retrieval using IoT, Weather determination results, Urban environment visualization, and Comparison study. Each of these elements plays a crucial role in validating the effectiveness and applicability of our proposed digital twin system for weather prediction and visualization in urban environments. Data retrieval using IoT is a basic step in our methodology, where we collect real-time weather data from IoT sensors strategically placed in various areas in Malang. This data collection is critical to providing accurate and up-to-date input to our weather prediction models.

The weather determination results section describes the results of applying fuzzy logic to the obtained data, showing how our system processes and interprets the input to predict weather conditions. Next, urban environment visualization translates the predicted weather conditions into a virtual representation of the Malang urban landscape. This visualization helps in comprehensively understanding the impact of various weather scenarios on the city environment. Finally, the comparison study provides an analysis of our model’s performance compared to existing weather visualization and simulation systems, highlighting strengths and potential areas for improvement.

4.1 Data retrieval using IoT

In this section, we will discuss the process of capturing weather data using IoT technology, which is the basis for adaptive visualization of urban weather conditions using digital twin technology.

Figure. 5 IoT device for weather monitoring

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Table 1. Examples of data retreival and defuzzification result

Experiment	Sub-district	Temperature (°C)	Humidity (%)	Wind (km/h)	Defuzzification	Weather
1	Blimbing	32	55	27	0.2	Regular rain
2	Blimbing	23	77	21	0.6	Sunny cloudy
3	Kedungkandang	27	79	24	0.6	Sunny cloudy
4	Kedungkandang	21	81	13	0.6	Sunny cloudy
5	Klojen	33	55	32	0.3	Drizzle
6	Klojen	24	83	23	0.6	Sunny cloudy
7	Lowokwaru	22	87	12	0.6	Sunny cloudy
8	Lowokwaru	34	67	23	0.2	Regular rain
9	Sukun	27	78	22	0.6	Sunny cloudy
10	Sukun	24	84	19	0.6	Overcast

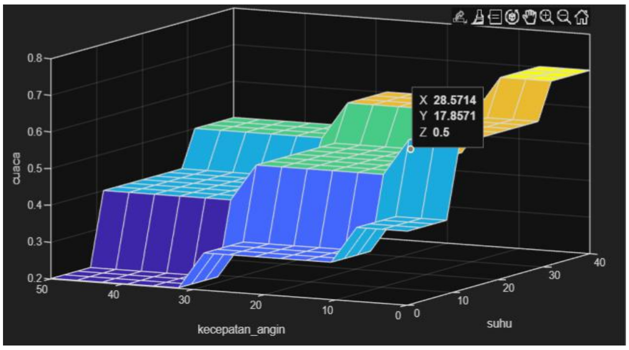

Figure. 6 Relationship between temperature (X) and wind speed (Y)

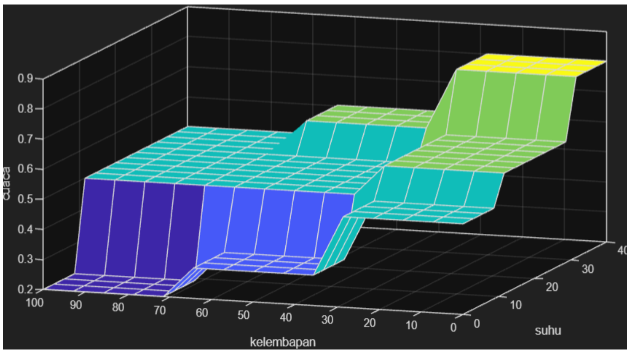

Figure. 7 Relationship between temperature (X) and humidity (Y)

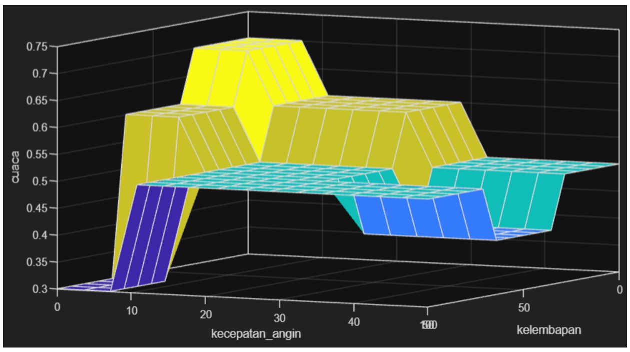

Figure. 8 Relationship between humidity (X) and wind speed (Y)

The assembly results of the IoT devices used in this research are shown in Fig. 5. This IoT device is designed to be mobile, with the aim of being easy to move and place in various strategic locations. This device is equipped with temperature, humidity, wind speed, and GPS sensors to ensure the data obtained is accurate and appropriate for the specific location in Malang City. The main purpose of using this mobile device is to collect weather data from various points in the city so that it can reflect variations in weather conditions in a more detailed and comprehensive manner.

We tested an IoT device for collecting data on weather conditions in five different sub-districts in Malang, as shown in Table 1. Several examples of data from temperature, humidity and wind speed sensors provide a visual depiction of the general weather conditions in each location. These findings provide important insights for accurate and adaptive weather visualization models, which are relevant for applications in IoT-based digital twin systems aimed at improving urban planning and response to weather conditions.

4.2 Weather determination result

This section discusses the test results of the Sugeno fuzzy method, which is used to determine weather conditions in the proposed digital twin system. This method is applied to ensure that the system can predict and visualize weather conditions accurately based on input environmental data obtained through IoT devices. Testing the Sugeno fuzzy method is very important to assess the system's performance and reliability in producing weather predictions that match real conditions in the field.

Testing the Sugeno fuzzy method is needed to find out whether this method has worked according to the requirements used in this research. Fig. 6 shows the relationship between temperature (X) and wind speed (Y). From this graph, it can be seen that variations in wind speed affect temperature changes in the observed area. Higher temperatures tend to occur at lower wind speeds in accordance with weather patterns in tropical regions such as Malang.

Next, Fig. 7 illustrates the relationship between temperature (X) and humidity (Y). This graph shows that humidity tends to be higher at lower temperatures and decreases as the temperature increases. This pattern reflects the general condition where higher temperatures usually cause more evaporation, which reduces air humidity.

Fig. 8 shows the relationship between humidity (X) and wind speed (Y). This graph indicates that higher humidity tends to occur at lower wind speeds. Strong winds can help reduce humidity by increasing the rate of evaporation.

These findings confirm that Sugeno's fuzzy method can capture the complex relationship between temperature, humidity and wind speed. This ability provides a strong foundation for adaptive weather visualization in digital twin systems. Visualizing these results helps clarify how various weather factors interact and influence overall environmental conditions.

The theoretical foundation for these results lies in the process described in Section 3.2, where the Fuzzy Sugeno method is employed. This method uses several steps of fuzzy logic principles to ensure mathematically sound results: First, the fuzzification process converts crisp input values (temperature, humidity, wind speed) into fuzzy sets, determining the degree of membership of each input in the fuzzy sets. For instance, temperature is divided into categories such as "cold," "warm," and "hot," with corresponding membership functions defined by linear equations. Next, the rule base defines how the input variables interact, with each rule in the Sugeno model specifying a mathematical function for the output based on fuzzy input values. The inference process combines these rules using methods like the min-max approach, where the minimum degree of membership among the inputs determines the rule's fulfillment. Finally, the defuzzification process converts the fuzzy set obtained from inference into a crisp output, typically a weighted average of the rule outputs. This structured approach ensures that the results are not just special cases but generalizable predictions grounded in fuzzy logic principles, providing robust and accurate weather visualizations based on real-time data from IoT sensors.

Furthermore, Table 1 also shows the defuzzification results of ten data collection experiments. These results show varying weather conditions in each sub-district based on measured temperature, humidity and wind speed. For example, in Blimbing District, at a temperature of 32°C, humidity of 55%, and wind of 27 km/hour, the system predicts weather conditions as Normal Rain with a defuzzification value of 0.2. On the other hand, in the same district with a temperature of 23°C, humidity of 77% and wind of 21 km/hour, the weather is predicted to be sunny and cloudy with a defuzzification value of 0.6.

Kedungkandang District showed a similar pattern with a prediction of sunny cloudy under conditions of higher temperature and humidity. At the same time, Klojen District recorded drizzle at a high temperature of 33°C and wind of 32 km/hour. Data from Lowokwaru and Sukun Districts also shows interesting variations, where high temperatures and humidity with lower winds generally predict sunny, cloudy weather.

This analysis shows that the Sugeno fuzzy method applied in the digital twin system can provide accurate weather predictions based on variations in input data. The resulting visualization of weather conditions can help city planning and management more effectively, providing the information needed to deal with changing weather conditions.

4.3 Urban visualization result

In this section, we will discuss the visualization results of the user interface and virtual environment used in the proposed digital twin system. Visualization is an important component in this research because it allows users to view and understand urban weather conditions more intuitively and interactively. This digital twin system is designed to present weather data collected via IoT devices in the form of adaptive and easily accessible visualizations so that it can support various analysis and decision-making needs in the context of urban environmental planning and management.

The results of the user interface visualization show how users can interact with the system to select sub-district areas, as shown in Fig. 9.

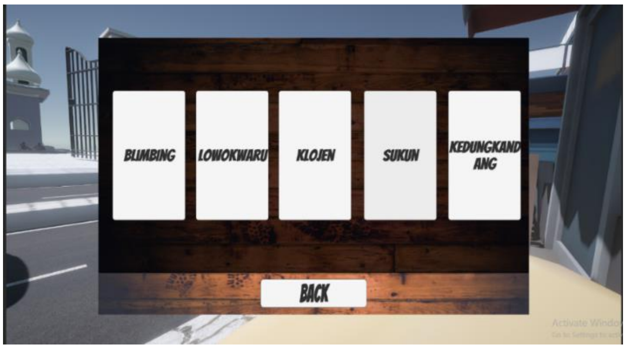

Figure. 9 User interface for selecting sub-district areas

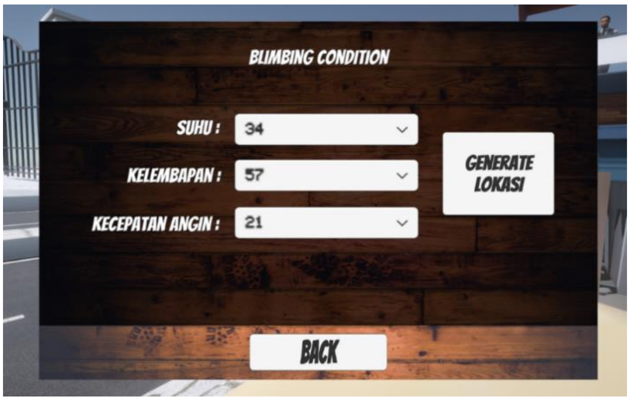

Figure. 10 User interface for filling in weather data

Users can also interact by filling in weather data, as shown in Fig. 10. The virtual environment used in this system provides a graphical representation of weather conditions in various locations in the city, which are visualized in three dimensions. Users can see how weather variables such as temperature, humidity, and wind speed affect the urban environment directly through this visualization.

Fig. 11 displays a visualization of the Sukun sub-district in sunny cloudy conditions, showing clearer weather with several clouds in the sky. Next, Fig. 12 shows a visualization of the Klojen sub-district in overcast conditions, providing a realistic picture of the weather situation, which is more gloomy and covered by thick clouds. Lastly, Fig. 13 shows a visualization of the Blimbing sub-district in somewhat cloudy conditions, depicting varying weather conditions with a combination of sunny and cloudy. Through this visualization, users can understand the impact of various weather conditions on the urban environment in more detail and comprehensively.

4.4 Comparison study

This research offers several significant advantages compared to previous research, as shown in Table 2. Several previous studies, such as those conducted by Holliman et al. [19] and Dembski et al. [20], although successful in the visualization of complex and comprehensive urban data, should have emphasized the adaptive aspect of their system. Holiman et al. focus on highly detailed visualization of pixel therapy using cloud computing, but these systems are not designed to respond adaptively to changing environmental conditions in real time. Instead, this research is designed to adaptively respond to changing urban weather conditions in real time, enabling continuous visualization updates based on the latest data from IoT sensors.

Research by Kikuchi et al. [21] and Lee et al. [23] demonstrated the successful use of Digital Twin technology for various urban applications, including flood visualization and individual mobility management. However, this research combines IoT technology with Digital Twin and the fuzzy sugeno method to manage urban weather data more efficiently. This integration enables real-time monitoring of weather conditions and more responsive visualization, something that previous research has yet to achieve fully.

Table 2. Comparison study

Name and Year of Reference	Object Discussed	Media Type	Technology and Methods Used	Adaptive	Interactive
[18]	Weather forecast and air quality	Digital Twin	IoT, Mobile Platform	Yes	Yes
[19]	Urban IoT data	Terapixel Visualization	Cloud Supercomputing, IoT	No	Yes
[20]	Urban mobility, wind flow	Digital Twin	Space Syntax, Urban Mobility Simulation	No	Yes
[21]	Flooded city visualization	Digital Twin, AR, Drone	AR, 3D Model, Drone	Yes	Yes
[22]	Individual mobility	Digital Twin, Unity3D	CCTV, IoT, License Plate Anonymization	Yes	Yes
[23]	Road and weather conditions	Digital Twin	IoT, 3D Visualization	Yes	Yes
[24]	Large-scale urban analysis	Unreal Engine	Procedural Generation, Big Data Analysis	No	Yes
[25]	Public participation in city planning	Digital Twin	3D Model, IoT, Online Platform	No	Yes
This Study	Urban weather conditions	Digital Twin	IoT, Fuzzy Sugeno, 3D Visualization	Yes	Yes

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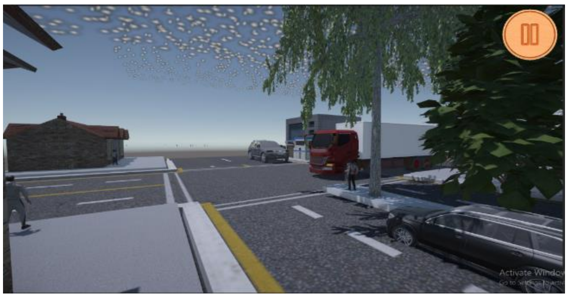

Figure. 11 Visualization of sunny cloudy weather in the Sukun sub-district area

Figure. 12 Visualization of cloudy weather in the Klojen sub-district area

Figure. 13 Visualization of somewhat cloudy weather in the Blimbing sub-district area

As done by Somanath et al. [24] and White et al. [25], this research also uses 3D visualization to improve user interaction and understanding of complex urban data. However, this research focuses more on the visualization of weather conditions in high detail that is adaptive to changes in real-time data, which provides a more accurate and relevant view of the urban environmental situation.

In addition to describing the features of each technique, it is crucial to emphasize the specific data supporting these comparisons. For instance, the adaptive capabilities of our system are evident through the real-time data collected from IoT sensors and processed using the fuzzy Sugeno method, as shown in the results in Section 4.2. This approach starkly contrasts with the non-adaptive visualization methods in studies like those by Holiman et al. [19], which do not account for real-time changes. Additionally, our study's integration of IoT with Digital Twin technology enables continuous updates and precise weather predictions. This is a significant advancement over the work by Kikuchi et al. [21], which focuses more on static flood visualization without incorporating real-time data.

Beyond technical merits, this research offers substantial practical benefits for city stakeholders. The ability to adaptively respond to changing weather conditions means that our system can aid in more effective and responsive city planning, particularly regarding environmental challenges such as urban heat islands. Furthermore, the high level of public participation and interactivity allows city residents to actively engage in monitoring and decision-making related to environmental conditions. Overall, this research provides a more integrative and adaptive solution compared to previous studies. By merging IoT technology, Digital Twin, and the Fuzzy Sugeno method, this research not only addresses the limitations found in prior studies but also introduces significant innovations in real-time urban weather visualization. Consequently, the outcomes of this research can significantly contribute to more efficient and sustainable city management and planning.

5. Conclusion

This study presents a system that integrates digital twin technology with the Fuzzy Sugeno method to develop an adaptive and real-time weather visualization model for urban settings. By utilizing real-time data collected from IoT sensors placed throughout the city, the system processes information on temperature, humidity, and wind speed to produce accurate and relevant weather visualizations. These visualizations cover a range of weather conditions, including heavy rain, regular rain, drizzle, overcast, cloudy, sunny cloudy, somewhat cloudy, and sunny. The findings from ten experiments, with temperature ranges from 21°C to 34°C, humidity from 55% to 87%, and wind speeds from 12 km/h to 32 km/h, indicated a dominant defuzzification value of 0.6, corresponding to sunny cloudy conditions.

The theoretical foundation of this study is grounded in fuzzy logic principles, particularly the Fuzzy Sugeno method. Fuzzy logic is well-regarded for its ability to handle uncertainty and non-linear relationships in data, making it suitable for interpreting complex environmental data. The Fuzzy Sugeno method, specifically, excels in providing precise outputs through its robust defuzzification process, which converts fuzzy inputs into clear, actionable weather predictions. This theoretical basis ensures that the system can adaptively and accurately visualize weather conditions in real-time, thereby enhancing urban environmental managemen.

Despite its promising results, this study has several limitations that warrant further investigation. One area for improvement is the reliance on the availability and accuracy of IoT sensor data, which can be affected by sensor placement and environmental factors. Additionally, the system's performance in extreme weather conditions, such as severe storms or heat waves, could have been more extensively tested. Future research should focus on enhancing the robustness of the system under diverse weather scenarios and expanding the scope to include more environmental variables. Moreover, incorporating advanced machine learning techniques could improve the system's predictive capabilities and adaptability. Further exploration into the integration of crowdsourced data could also provide a more comprehensive understanding of urban weather patterns, leading to even more precise and reliable visualizations.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Y.M. Arif; methodology, Y.M. Arif, T. Kusumadewi, and A.F. Karami; software, Y.M. Arif and B. G. F. A'rof; validation, Y.M. Arif, T. Kusumadewi, and A.F. Karami; formal analysis, Y.M. Arif, B. G. F. A'rof, and T. Kusumadewi; investigation, Y.M. Arif and T. Kusumadewi; resources, Y.M. Arif, B. G. F. A'rof, and A.F. Karami; data curation, Y.M. Arif and B. G. F. A'rof; writing—original draft preparation, Y.M. Arif; writing—review and editing, Y.M. Arif, L. Wijayanti, and M. Mulyadi; visualization, A.F. Karami; supervision, L. Wijayanti and M. Mulyadi; project administration, T. Kusumadewi; funding acquisition, Y.M. Arif.

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