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Design of a Radiosonde System for Air Quality Monitoring in the Tangerang City Area

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A B S T R A C T

Tangerang City, located in Banten Province, Indonesia, experiences high rainfall levels that often lead to damaging floods. Climate change has exacerbated these disasters with increasingly unpredictable weather extremes. To address these challenges, upper-air observations using radiosondes are crucial for real-time atmospheric monitoring. Radiosondes effectively measure meteorological parameters such as air pressure, temperature, and humidity when flown into the atmosphere by balloons. This study developed a cost-effective and easily implementable radiosonde system to enhance meteorological data collection in Tangerang City. Thus, the system supports accurate weather analysis and improves disaster management and environmental decision-making in the region.

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1. INTRODUCTION

Tangerang is one of the main buffer cities in the Greater Jakarta metropolitan area, occupying the third position after Bekasi City and Depok City in West Java. According to the Central Bureau of Statistics (BPS) in 2024, the population of Tangerang City will reach 1963.97 thousand people. Tangerang City is located in Banten Province, Indonesia, with geographical coordinates of approximately 6 ° 10 ′ N and 106 ° 38 ′ E. The city is bordered by Jakarta on the one hand, and on the other hand, by Jakarta on the other. The city borders Jakarta to the east, Tangerang Regency to the west and north, and South Tangerang City to the south. Tangerang has a strategic role as one of the main supports of the capital city of Jakarta in various aspects, including economy, transportation, and housing.

Early warning systems for air quality have progressed rapidly thanks to the Internet of Things technology, which enables real-time monitoring of air pollutants such as PM2.5, NO2, and CO through interconnected sensors [1][2]. Recognising the significance of monitoring air quality and providing precise and fast data to the public. Almost every work site has the possibility of hazards, ranging from the materials used, the way of working, to the waste produced (liquid, solid, and gas). If not handled properly, this way of working can pose a serious threat to the safety and health of the workforce [3][4][5].

Since the period of the 1950s, under the guidance of the World Meteorological Organisation (WMO), radiosonde measurements have been carried out to produce good quality vertical data that can measure temperature, humidity and wind data in an area measured by the radiosonde [6][7]. The use of radiosonde data can be used for weather forecasting [8], re-analysis of atmospheric history [9], calibration of data from satellites [10], and research on extreme regions [11]. Specifically, temperature information from radiosondes is crucial in assessing and linking atmospheric warming patterns [12], measuring atmospheric moisture levels and water vapour patterns [7], and analysing atmospheric instability and buoyancy changes [13]. Internet- based

According to data from the Central Bureau of Statistics (BPS), the level of rainfall in Tangerang City in the period 2021-2023 is quite high. The highest rainfall occurred in February 2021 at 446.30 mm [14]. Global weather changes can affect hydrological aspects, such as very high rainfall and variations in rainfall patterns, both of which lead to increased flooding in urban areas and negative impacts on existing city infrastructure [15]. This leads to loss of assets, especially infrastructure and household property, as well as impacts on people and the economy, especially income in the industrial and transport sectors, and disruptions in trade activities [16].

Air quality monitoring has been done by many researchers before [17] conducted research related to air quality where they created an air quality monitoring system that predicts pollutants and measures air pollution levels. In addition, air quality monitoring techniques are carried out differently which are spatiotemporal based which can predict air pollution by considering the spatial distribution and interaction characteristics between regions [18].

Julio Buelvas et al. [19] focused their innovation on data quality in IoT-based air quality monitoring systems. They focus on improving data accuracy and precision by means of sensor calibration techniques. Research by Ade Silvia Handayani et al [20] created a multi-sensor network to monitor air in a closed parking area, especially motor vehicle exhaust gas. This IoT system provides real-time data with high accuracy, helping users avoid areas with high levels of air pollution.

There are many methods developed by researchers to facilitate air quality monitoring, namely the SVM method [21], LSTM model [22][23], using ICEEMDAN, WOA, and ELM techniques [17], spatial spill techniques and cognitive fuzzy models [18], internet-based [24], [25], [26], [27].

2. RESEARCH METHOD

The method applied in this study is through a literature review, which involves collecting and reviewing various relevant reading sources. These sources consist of books, academic journals, research reports, articles, and other documents related to the issue under study. These sources were then used as references for the design of the Radiosonde System for Air Quality Monitoring in Tangerang City.

In addition, this method also includes a critical assessment of the existing literature to find gaps in the research, as well as summarising previous results to strengthen a more in-depth analysis. This approach aims to gain in-depth insight into the topic of study and create a strong theoretical foundation to support the research results.

2.1 Place of Research

Fig. 1. Place of research map

The research was conducted in Semarang City, Central Java. Semarang City is located between 6°50‘7°10’ South latitude and 109°35‘- 110°50’ East longitude. To the west, Semarang City is bordered by Kendal Regency, to the east by Demak Regency, to the south by Semarang Regency.

2.2 Research Stages

The research stages carried out in this study can be seen in Fig. 2.

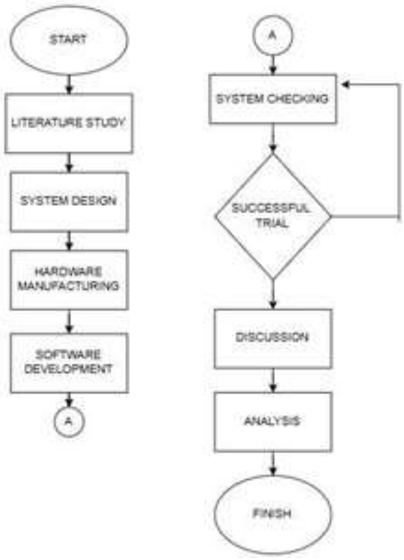

Fig. 2. Flowchart of Research Stages

The flowchart shown in Fig. 2. illustrates the sequence of work in the research process undertaken. The first stage is the system study, which includes the theoretical basis and review of the systems that support this research. This system study is important to understand the background and scientific context of the research to be conducted. After that, the next stage is system design, which is a detailed plan for making the system in this research. At this stage, the initial design of the system is made by considering all the needs and technical specifications that have been identified.

The next stage is hardware manufacturing, which involves making the necessary hardware for the system. This includes the selection and assembly of electronic components, as well as ensuring all the parts work well together. Next, the software is created, which includes developing software for the microcontroller and creating a graphical user interface (GUI) programme. The software is in charge of controlling the hardware and allowing users to interact with the system effectively.

2.3 Work System

The system starts with sensors that detect temperature, relative humidity (RH), and air pressure parameters. In addition, the GPS system will obtain location and altitude data of the radiosonde transmitter. All this data is then sent to the receiver using radio waves at a frequency of 433 MHz.

The receiver receives the signal and processes it into data that can be displayed on a PC. Thus, users can know the data of temperature, RH, air pressure, wind direction and speed, as well as the location and altitude of the radiosonde transmitter. This system is designed to monitor air quality in the Tangerang City area, so as to provide accurate real-time information about local atmospheric conditions. This information is very useful in weather analysis and mitigation of potential disasters such as floods, especially considering the high rainfall and flood vulnerability in Tangerang City. This easy-to-implement and low-cost system is expected to be adopted by various observation stations in the region, to increase meteorological data density and support better decision-making in environmental management.

3. RESULT AND DISCUSSION

3.1 System Design

The designed system is divided into two main components, namely the transmitter and receiver. The transmitter consists of several elements, including a temperature sensor, relative humidity (RH) sensor, air pressure sensor, GPS system, microcontroller, telemetry module, and battery. Meanwhile, the receiver consists of a receiving antenna, telemetry module, and microcontroller. The sender is planned to be mounted on a vehicle, such as a balloon filled with helium gas, for flight purposes.

Various parameters such as temperature, RH, air pressure, wind direction and speed, and the location and altitude of the sender will be measured using sensors and GPS, and then the collected data will be sent to the receiver. At the receiver, a laptop or PC is used to display the results of the measurements that have been made. The measurement data can also be read and stored on the device. The system block diagram shows the overall structure of this system.

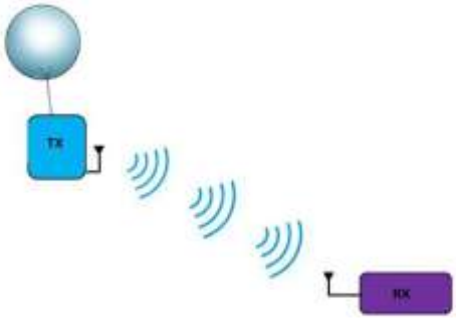

Fig. 3. Radiosonde system

3.2 System Components

The system consists of transmitter and receiver parts. The components in the transmitter system consist of sensors, GPS, microcontroller and telemetry module. Figure 3 shows the block diagram of the transmitter system.

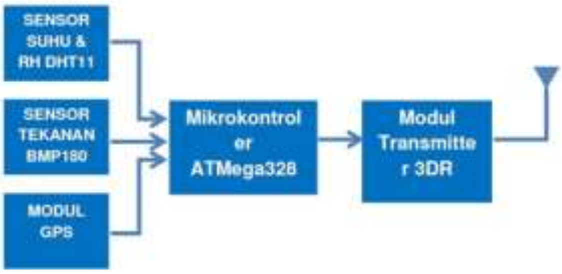

Fig. 4. Radiosonde components diagram

In Fig. 4, the DHT11 sensor, BMP180 sensor, and GPS module act as components that generate the data needed to measure temperature, relative humidity (RH), air pressure, and location parameters. The information obtained from these sensors will be transferred to the ATMega328 microcontroller for further processing. After going through the processing stage, the data will be sent through a 3DR- type transmitter module operating at a frequency of 433 MHz.

Fig. 5 provides a visualisation of the entire transmitter system that has been successfully assembled and prepared for use. In the figure, it can be clearly seen how the components are arranged and connected to each other, showing that the transmitter system has been successfully completed and is ready to perform its functions.

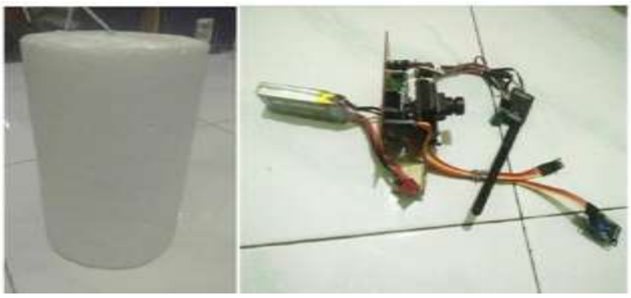

Fig. 5. Transmitter casing and transmitter without casing

Fig. 6. Receiver system

Fig. 6 is a visual representation of the receiver system block diagram, which operates on the principle of receiving the signal sent by the transmitter through the receiving antenna. The next process involves channelling this signal to the ATMega328 microcontroller, where it is processed to conform to a format that can be displayed. Once processed, the data is ready to be displayed on a laptop or PC screen for further observation and analysis. In other words, this block diagram illustrates the series of processes from signal reception to data presentation that can finally be interpreted by the user through a computer interface.

Fig. 7. Built receiver system

Fig. 7 is a visual representation of the receiver system that has been designed and built. In the figure, the components that form part of the receiver system can be seen, which include the receiving antenna, telemetry module, and microcontroller. This entire system has been successfully assembled and prepared to receive and process the signals received from the transmitter. Fig 6 thus gives an overview of how the receiver system has been completed and is ready to be used in its application context.

3.3 System Testing

Testing the radiosonde system includes several important steps, namely sensor calibration, telemetry system communication distance testing, and transmitter power consumption analysis.

a. Communication Distance Testing

This test aims to determine the maximum distance at which the telemetry system can function properly. Table 1 shows the data from the communication distance test of the radiosonde system.

Table 1. Communication Distance Testing Results

Height (metres) Success rate	Height (metres) Success rate
100	Success
1000	Success
2000	Success
3000	Success
4000	Success
5000	Success
6000	Success
7000	Success
>7000	Success

The data in Table 1 show that the radiosonde communication system, when flown by balloon, works well under vertical Line of Sight conditions up to an altitude of 7000 metres above sea level. Communication is lost when the altitude exceeds 7000 metres.

b. Sensor Calibration

Calibration is the process of comparing the measurement results of observation tools with known and tested standard values. In the radiosonde system for monitoring air quality in Tangerang City, calibration is important to ensure the accuracy and consistency of temperature, relative humidity (RH), and air pressure sensor data. This process helps identify and correct inaccuracies, so that the resulting data is reliable.

Sensor testing aims to ensure the sensors function properly under the expected conditions of use. In this radiosonde system, testing includes sensitivity, response time, reliability and stability of the sensor. This is important to ensure that the sensor is capable of producing accurate and consistent data in various situations.

Sensor testing and calibration ensures that the radiosonde system can provide accurate real-time data, which is crucial for weather analysis and potential disaster mitigation in Tangerang City.

c. Telemetry Testing

Telemetry testing on the radiosonde system aims to determine whether the transmitter and receiver components can function properly in the process of monitoring air quality in the Tangerang City area. This process involves sending data from the transmitter attached to the radiosonde to the receiver located at the monitoring station. The success indicator of this system test is the receiver's ability to receive the data intact and save it in .txt or .xls format. This is important to ensure that the data received can be processed and analysed further.

Successful telemetry testing showed that the radiosonde system was able to accurately transmit critical information such as temperature, relative humidity (RH), air pressure, wind direction and speed, and location and altitude. This data is invaluable for monitoring air quality in Tangerang City, providing accurate real-time information on local atmospheric conditions. In addition, the system can support weather analysis and mitigation of potential disasters such as flooding, given the high rainfall and flood vulnerability in the region. Therefore, telemetry testing not only ensures the technical reliability of the radiosonde system but also supports better decision-making in environmental management in Tangerang City.

3.4 Analysis of Test Result

a. Data Transmission Success

Analysis of the test results is carried out to evaluate the overall performance of the radiosonde system after going through the design and testing stages. The following are some of the main points discussed in this analysis:

The test results show that the radiosonde system is able to transmit data up to an altitude of 7000 metres above sea level with a high success rate. Communication was lost when the altitude exceeded 7000 metres. This shows that the telemetry system works well under vertical Line of Sight conditions, but needs improvement for communication at higher altitudes.

b. Sensor Data Accuracy

Sensor calibration shows that the temperature, relative humidity (RH), and air pressure sensors provide accurate and consistent results according to known and tested standard values. The calibration process helps identify and correct inaccuracies, making the resulting data reliable for air quality analysis.

c. System Reliability

Sensor testing ensures that the sensors function properly under expected conditions of use, including sensitivity, response time, reliability and stability of the sensors. The system is able to provide accurate real-time data, which is crucial for weather analysis and potential disaster mitigation in Tangerang City.

d. Ease of Implementations

The radiosonde system is designed to be easy to implement and low cost. This is expected to increase the adoption of the system by various observation stations in Tangerang City area, in order to increase meteorological data density and support better decision-making in environmental management.

e. Potential Use for Disaster Mitigations

Data obtained from radiosonde systems are very useful for weather analysis and mitigation of potential disasters such as flooding. Real-time information on local atmospheric conditions can help in responding to emergency situations more quickly and effectively, especially considering the high rainfall and flood vulnerability in Tangerang City.

4. CONCLUSION

This research successfully designed and developed a radiosonde system to monitor air quality in Tangerang City. The system, which consists of sender and receiver components, is proven to be able to measure and transmit meteorological data accurately up to an altitude of 7000 metres. The sensors used are well calibrated, producing reliable data for weather analysis and disaster mitigation. The system is also easy to implement and low cost, enabling wider adoption by local observation stations, thereby increasing meteorological data density and supporting better decision-making in environmental management.

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Utilization of Himawari-9 and Radiosonde Weather Satellite Data in Heavy Rainfall Analysis (Case Study: Semarang, 14 March 2024)

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A B S T R A C T

The heavy rainfall event that hit Semarang City on 14 March 2024 caused flooding at several points. To understand the cause of this event, a comprehensive meteorological analysis is required. This research utilises Himawari-9 weather satellite data with RGB, day convective storm and 24-hour microphysics methods, as well as upper air observations using radiosonde at 12 UTC in the Semarang area. The use of this method is effective in knowing the atmospheric conditions in the Semarang area. The results of observations with the RGB method show cloud conditions that cause heavy rain with high intensity. Observations with the day convective storm method detect convective clouds that have the potential to cause heavy rain. The 24-hour microphysics method identifies High Cumulonimbus, Dense Cirrus, and Thick Cirrus cloud types that can cause heavy rain. Upper air observations with radiosonde at 12 UTC showed the early phase of severe weather in the Semarang area. The results of this study confirm the importance of satellite and radiosonde data integration in predicting and analysing heavy rain events for hydrometeorological disaster risk mitigation.

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1. INTRODUCTION

Climate change and extreme weather variability have become increasingly prevalent in many parts of the world, including Indonesia, where these phenomena are intensifying in frequency and severity. This trend is further exacerbated by human activities such as deforestation, industrial emissions, and urbanization, which significantly magnify the adverse effects of climate change. Climate change is not merely a gradual shift in temperature but a catastrophic force that accelerates extreme weather events, both in terms of frequency and intensity. These disruptions contribute directly to global temperature rises, the warming of oceans, rising sea levels, and the intensification of severe weather events such as droughts and floods [1]. The consequences of these changes are far-reaching, disrupting ecosystems, agriculture, and water resources, all of which pose significant threats to sustainable development and the well-being of communities.

Among the most pressing challenges posed by climate change is the phenomenon of heavy rainfall, which has become one of the key concerns for natural disaster mitigation and regional development planning, particularly in densely populated urban areas like Semarang. As cities continue to grow and expand, urban planning often fails to keep pace with the demands of the increasing population, leading to inadequate drainage systems and poor infrastructure. These deficiencies in urban planning exacerbate the impacts of heavy rainfall, resulting in frequent flooding that affects daily life, damages property, and displaces communities. Furthermore, the consequences extend beyond physical damage, as the flooding increases the risk of public health issues, including the spread of waterborne diseases, creating significant challenges for public health authorities and urban planners alike.

The uncertainty surrounding rainfall intensity and duration adds an additional layer of complexity to the situation, with implications for transportation safety. Rainfall events that are difficult to predict lead to a higher frequency of accidents, particularly during peak traffic hours. Reduced visibility, slippery roads, and disruptions to public transportation schedules all contribute to making urban mobility more difficult and dangerous during rainy periods [2]. For example, sudden rain showers can create hazardous conditions, making it harder for commuters to navigate the city safely. This underscores the importance of accurate and timely weather predictions, as they are essential to mitigating the risks associated with such unpredictable weather patterns. Meteorologists often rely on various parameters to describe weather and climate, with rainfall intensity or volume being among the most critical of these [3]. Effective measurements and forecasts are crucial for minimizing the adverse effects of extreme weather events, particularly in urban environments.

In regions located at higher latitudes, the effects of climate change on snowfall extremes and freezing rain differ significantly from its impact on rainfall extremes, underscoring the need for more in-depth studies and region- specific research [4]. This distinction highlights the complexities of how climate change affects different geographic regions, stressing the importance of localized research to fully understand these phenomena and to tailor appropriate mitigation strategies.

Weather satellites such as Himawari-9 have become invaluable tools in providing critical meteorological data, including atmospheric conditions, which are vital for monitoring and predicting precipitation, especially in remote or hard-to-reach areas [5]. These satellites play a crucial role in improving our understanding of atmospheric dynamics and enhancing the accuracy of weather forecasts. The Himawari-8, a next-generation Japanese geostationary meteorological satellite, was launched on October 7, 2014, and became fully operational on July 7, 2015. On December 13, 2022, the operational control was transferred to the Himawari-9 satellite [6]. With their advanced imaging and monitoring capabilities, these satellites have revolutionized meteorological observations, providing high-resolution data that are indispensable for climate research, disaster management, and efforts to mitigate the impacts of extreme weather events. The ability to track and predict weather patterns with such precision has made significant contributions to improving disaster preparedness and response, especially in regions prone to heavy rainfall and flooding.

2. RESEARCH METHOD

Key objectives included analyzing the capability of satellite and radiosonde data in detecting convective cloud formations, assessing the accuracy of RGB methods in identifying severe weather conditions, and evaluating the effectiveness of upper-air observations in predicting heavy rainfall events.

a. Location and Time of Research

The research was conducted in Semarang City, Central Java. Semarang City is located between 6°50‘7°10’ South latitude and 109°35 - 110°50’ East longitude. To the west, Semarang City is bordered by Kendal Regency, to the east by Demak Regency, to the south by Semarang Regency.

b. Band Determination

The data obtained came from the archives of the Meteorological Climatology and Geophysics Agency (BMKG) through the Japan Meteorological Agency (JMA). In this study, Band 10 (7.3 m) - Band 8 (6.2 m), Band 13 (10.4m) - Band 7 (3.9 m) and Band 3 (0.64 m) - Band 5 (1.6 m) were used. Band 13 (10.4m) - Band 15 (12.4 m), Band 11(8.6m) - Band 13 (10.4 m) / Band 11 (8.6 m) - Band 14 (11.2 m).

c. RGB Methods

In this research, the RGB (Red Green Blue) method is used which is implemented in the SATAID application. The RGB method is Day Convective Storm and 24 Hours Microphysics. The SATAID (Satellite Animation and Interactive Diagnosis) application is an application for processing binary type data from satellite imagery in real time and can be accessed easily [7]. In this study, the SATAID application was used to determine the type of clouds in rain events in Semarang City on 14 March 2024 at 7 to 12 UTC.

d. Day Convective Storm Method

The RGB method is used to identify convective clouds during the day. Day Convective Storm uses Band 10 (7.3 m) - Band 8 (6.2 m), Band 13 (10.4 m) - Band 7 (3.9 m) and Band 3(0.64 m) - Band 5 (1.6 m).

Color	Interpretation
	Deep precipitating cloud (precipitation is not necessarily reaching the ground) - high-level cloud, large ice particles
	Deep precipitating cloud (Cb cloud with strong updrafts and severe weather)* - high-level cloud, small ice particles *or thick, high-level lee cloudiness with small ice particles
	Thin cirrus cloud (large ice particles)
	Thin cirrus cloud (small ice particles)
	Ocean
	Land

Fig. 1. Classification of Day Convective Storm.
Source: Meteorological Satellite Centre (MSC) of JMA. Himawari Day Convective Storms RGB Quick Guide.

The bright yellow colour is identified as Cumulonimbus clouds carrying small ice particles, while the red colour contains high ice particles. Both clouds are clouds that bring severe weather.

e. 24H Microphysics Method

The 24H Microphysics method is used to analyse convective clouds at night (Abay and Haryanto, 2021). 24H Microphysics uses Band 13 (10.4m) - Band 15 (12.4 m), Band 11(8.6 m) - Band 13 (10.4 m) / Band 11 (8.6 m) - Band14 (11.2 m).

Color	Interpretation
	Thick, high and cold ice clouds
	Thick water clouds
	Clouds with small particles
	Thin cirrus clouds
	Dust (yellow sand)
	Sands with quartz mineral

Fig. 2. Classification of 24H Microphysics.
Source: Meteorological Satellite Center (MSC) of JMA. Himawari 24H Microphysics RGB Quick Guide.

The brick red colour in Fig. 2 shows that the cloud is a cumulonimbus cloud which brings bad weather.

f. Data Retrieval

To obtain comprehensive and accurate data on air weather conditions over the city of Semarang, satellite imagery from the Himawari-9 satellite was employed, in addition to upper air observation results obtained from the Wyoming Sounding on 14 March 2024. The Himawari-9 equipped with advanced imaging sensors, provides high-resolution images that are vital for tracking cloud formations, weather patterns, and atmospheric phenomena. The upper air observation data were captured through the use of a radiosonde, which is a sophisticated device mounted on a weather balloon to collect detailed meteorological data as it ascends through various layers of the atmosphere.

This device measures key atmospheric parameters such as pressure, temperature, and relative humidity, providing valuable insights into the vertical structure of the atmosphere [8,9]. Radiosondes have become an essential tool in atmospheric research, allowing researchers to acquire real-time, high-quality data that is critical for weather forecasting and climate studies. Numerous studies have effectively utilized radiosonde data in conjunction with other meteorological data to assess the accuracy of forecasting models, contributing significantly to the advancement of weather prediction technologies and climate modeling [10-13].

3. RESULT AND DISCUSSION

3.1 Day Convective Storm

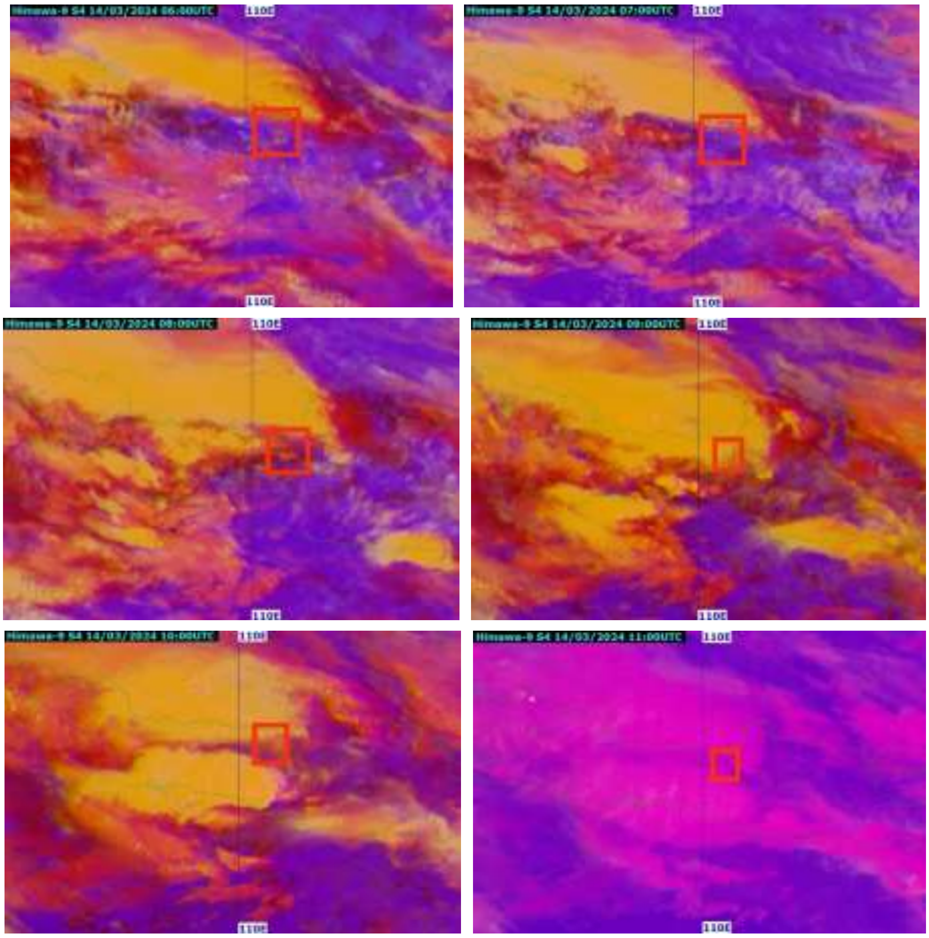

Fig. 3. Himawari-9 Day Convective Storm RGB Satellite Image on 14 March 2024 at 06.00- 11.00 UTC

3.2 24- Hour Microphysics

The system consists of transmitter and receiver parts. The components in the transmitter system consist of sensors, GPS, microcontroller and telemetry module. Figure 3 shows the block diagram of the transmitter system.

The red colour in the image above indicates thick clouds with high peaks (cumulonimbus clouds), while the black colour indicates thin high clouds (cirrus clouds). At 12.00 UTC, cumulonimbus clouds were seen covering the Semarang City area (white coloured box). This continued until at 17:00 UTC the cumulonimbus clouds covering the Semarang City area began to decay and were replaced by cirrus clouds.

3.3 Wyoming Sounding (Radiosonde)

Based on the data obtained from the Wyoming Sounding website on 14 March 2024 at 12:00 UTC, specifically from the Juanda Meteorological Station, several meteorological parameters were analyzed to assess the potential for severe weather in the Semarang City area. The Showalter Index (SI) resulted in a value of 0.38, indicating the presence of conditions favorable for thunderstorms. A value above 0 suggests the atmosphere's instability, which can lead to the formation of convective storms. The Lifted Index (LI), another important indicator of atmospheric instability, recorded a value of -1.21, signifying an unstable condition that enhances the potential for lightning activity. A negative LI value indicates that the air mass is relatively warmer and more buoyant than its surrounding environment, increasing the likelihood of upward motion and thunderstorms. Additionally, the K Index (KI), which takes into account temperature and humidity profiles to predict thunderstorm development, yielded a value of 38.10, pointing to a fairly high potential for thunderstorms. The SWEAT index, which assesses the likelihood of severe weather by evaluating wind patterns and moisture availability, reached 301.20, further suggesting a heightened risk of thunderstorms. The Convective Inhibition (CIN) parameter, which measures the resistance precipitation. These methods revealed the presence of such clouds over Semarang, indicating the likelihood of severe weather conditions.

Additionally, data from upper-air observations, specifically from the Radiosonde, provided critical insights into the atmospheric conditions above the city. The Radiosonde data, which measures key variables such as temperature, pressure, and humidity as the balloon ascends through the atmosphere, also pointed to the potential for heavy rainfall in Semarang. The combination of these observational techniques, which included both cloud-based monitoring and upper-air data, highlighted the severe nature of the weather event. The data suggested a high probability of intense rainfall, and ultimately, the heavy rain that followed caused significant flooding in multiple parts of Semarang City, overwhelming drainage systems and affecting daily life. These methods, together with real-time weather observations, allowed meteorologists to predict the heavy rain with greater accuracy, although the intensity of the rainfall still resulted in considerable local impacts.

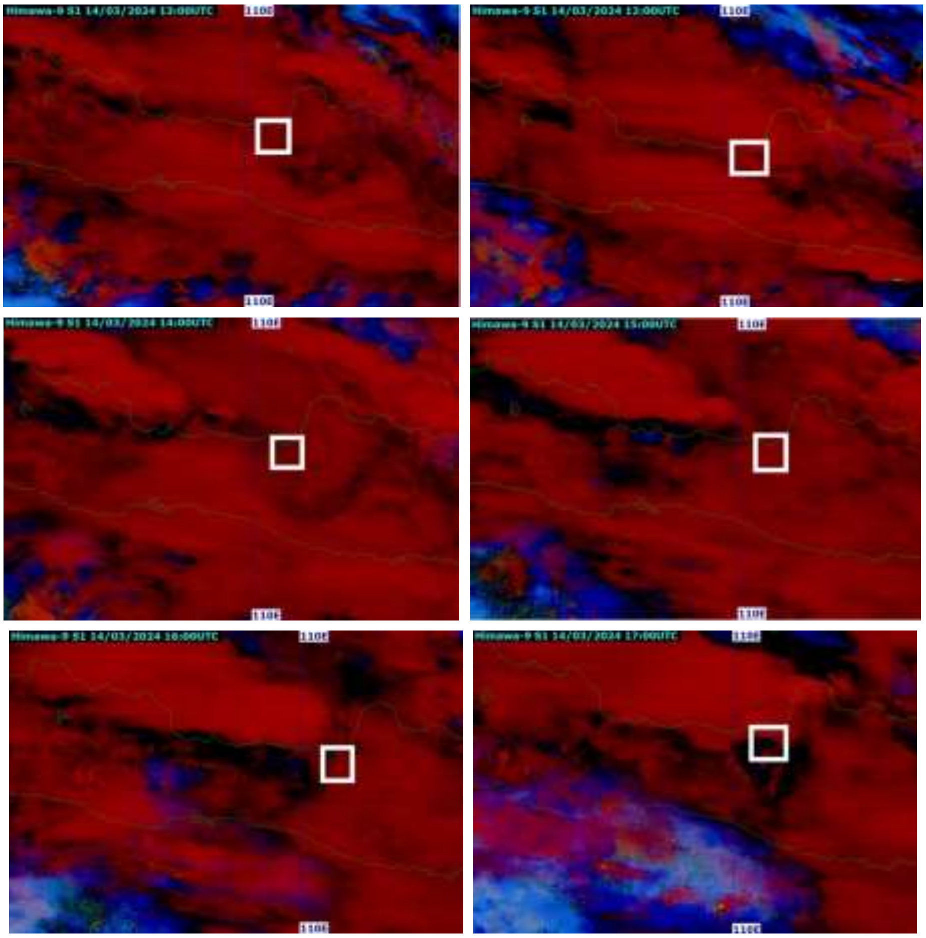

Fig. 4. Himawari-9 24-Hours Microphysics RGB Satellite Image on 14 March 2024 at 12.00-17.00 UTC.

4. CONCLUSION

On 14 March 2024, Semarang City experienced a significant weather event, as heavy rainfall led to widespread flooding in several areas across the city. This extreme weather phenomenon was identified and monitored through various meteorological methods, including the use of RGB (Red, Green, Blue) composite images, which are commonly employed to analyze weather conditions in satellite imagery. Specifically, the day convective storm and 24-hour microphysics methods were utilized to examine the formation and movement of convective clouds, which are often associated with intense to the upward movement of air, was -15.69, indicating an environment conducive to severe weather, as CIN values close to or below zero suggest limited inhibition of convection. Finally, the Convective Available Potential Energy (CAPE), a measure of the potential energy available to fuel storm development, recorded a value of 662.89, indicating a moderate to high potential for storm formation. With these parameters showing significant instability and favorable conditions for thunderstorm development, the Semarang City area on 14 March 2024 at 12 UTC was at risk for heavy rainfall and severe weather conditions, aligning with the observed heavy rain later that day.

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Literature Review: Performance Analysis of CNN, LBP, and Haar Cascade using FER-2013 for Facial Emotion Recognition

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A B S T R A C T

The rapid progress in artificial intelligence is transforming how humans and computers interact, with facial expressions being key markers of human emotions. Since facial expressions change dynamically during communication, they offer insights into emotional states and have attracted significant research interest. However, detecting emotions through facial recognition is challenging due to individual differences in expressions, varied lighting conditions, and different facial orientations. These challenges highlight the need for models that can effectively address these issues to improve detection accuracy. This literature review explores several commonly used algorithms for emotion detection via facial recognition, including Convolutional Neural Networks (CNN), Haar Cascade, and Local Binary Pattern (LBP), with the FER2013 dataset serving as the basis for analysis.

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1. INTRODUCTION

Rapid developments in artificial intelligence play a significant role in relation between human-computer interaction. The face plays an important role in conveying human emotions. Changes to facial expressions during communication are initial indicators of emotional state, making them a significant area of interest for most researchers [1]. The application of emotion detection based on facial recognition has challenges that include various special characteristics of facial expressions at the individual level, lighting conditions, and facial positions which are an object for the development of a model that will be able to overcome them so that a model becomes more accurate [2].

The application of emotion detection based on facial recognition has challenges that include various special characteristics of facial expressions at the individual level, lighting conditions, and facial positions which will be an object for the development of a model that will be able to overcome them so that a model becomes more accurate. In this literature review, there are several algorithms for detecting human emotions through popular facial recognition Methods such as CNN, Haar Cascade, and Local Binary Pattern (LBP) with the FER2013 as a dataset.

The application of this technology has the potential to help in various sectors, such as mental health, behavioral analysis, and surveillance systems, for employees who will be able to monitor the performance of BMKG employees who require high performance in accuracy and precision in intense work situations.

2. RESEARCH METHOD

Facial expression-based emotion recognition systems are often trained using machine learning techniques. A commonly used model is Deep Neural Network, especially Convolutional Neural Network (CNN), for classification and identification purposes.

a. Conculutional Neural Network

CNN (Convolutional Neural Network) are artificial neural network algorithm that is particularly useful in the field of image processing such as object recognition, image classification, face recognition and other computer vision-based tasks. CNN works by taking important features in the data, such as particular patterns on the face, and preventing overfitting through dropout and max polling [3].

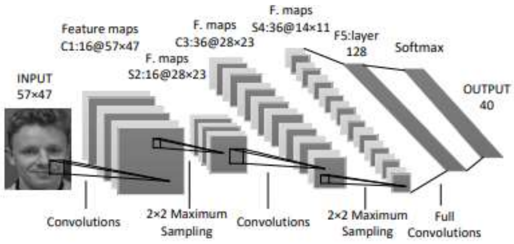

Fig. 1. CNN Architecture

The CNN architecture consists of an input layer, a first convolution layer to filter the input results with a kernel method, a ReLu layer to activate the activation function. followed by a pooling layer to simplify the feature map, another convolution layer with a corresponding pooling layer, then a fully connected (dense) layer [4]. Fig. 1 show the architecture of CNN.

b. Haar Cascade

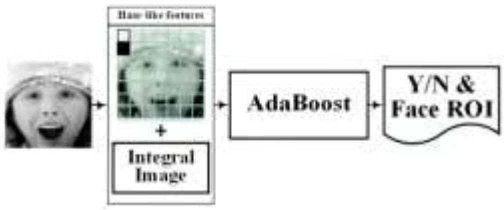

Fig. 2. Haar Cascade Dataflow

Haar cascades using Haar feature by subtracting the pixel value in the blank area from the pixel value in the write area.

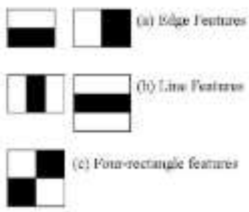

Fig. 3. Haar Cascade Feature

The face detector is based on a 24 x 24 grid. From this base detector, there are about 160,000 potential Haar-Like Features [7]. In Face recognition, the algorithm calculates the difference between pixel sums in these rectangular regions to detect object features, such as eyes or a nose in the case of face detection. Figure 4 shows the schematic of the detection cascade with N stages. The detection cascade is designed to reduce a large number of negative examples using minimal processing.

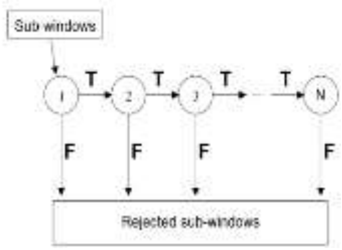

Fig. 4. Cascade Detection

Haar cascade classifiers use a multi-stage process to eliminate non-object regions early, ensuring efficient processing. Each stage contains a classifier that filters out non-target regions, only allowing those likely to contain the object to proceed to the next stage. This cascade improves the computational efficiency of object detection [8].

c. Local Binary Pattern

Local Binary Pattern (LBP) is an algorithm based on texture descriptors for texture classification and is widely used in image analysis, including facial expression recognition. LBP works by analyzing the pixel intensity pattern into a binary number (hence the term "binary pattern"[9].

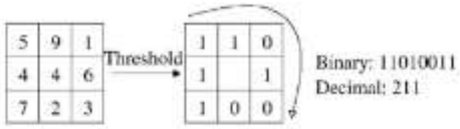

Fig. 4. Basic LBP operator

LBP was used as a general texture descriptor. The operator labels each pixel of the image by comparing the 3x3 neighborhood with the value of the center pixel and making it a binary number. The binary value is obtained by reading clockwise, starting from the upper left neighbor, as shown in the following Fig. 5.

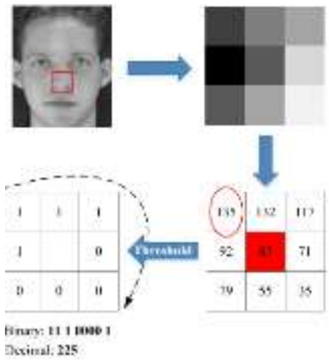

Fig. 5. LBP

To recognize facial expressions, the face image is divided into several small segments. The Local Binary Pattern (LBP) histogram is then computed for each segment. These histograms are combined into a single feature vector that captures spatial information, retaining details about local texture and the overall shape of the face [10].

d. FER-2013

FER-2013 is a datasheet containing 35,887 facial images that are differentiated based on seven emotional expressions namely: happiness, disgust, fear, anger, sadness, neutral, and surprise.This dataset includes images taken from the frontal position of the face with various expressions[11].

Fig. 6. Expression FER-2013

In Fig. 7 showing the distribution of facial expressions in the FER-2013 dataset. In this expression distribution, there is an uneven distribution of 7 expressions in the dataset where the disgusted expression has the smallest relative portion compared to other categories.This can lead to bias in certain classes and become a challenge in model development[12].

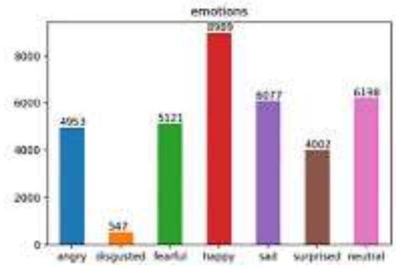

Fig. 7. Distribution of facial expression characteristics in FER 2013

e. Face Recognition

Facial expressions play a significant role in determining a person's emotional state. Parts of the face such as the eye area play a role in recognizing the emotions of sadness and fear. While the mouth is dominant in happiness and disgust. Analysis based on facial action units (AUs) shows that each emotion can show a specific combination of AUs. These findings can be applied to develop emotion recognition algorithms in computer vision [13].

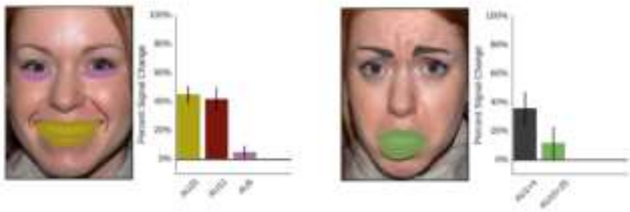

Fig. 8. Facial action Unit

Emotion classification processing is generally divided into data gathering, data pre-processing, advanced extraction, training, and validation, then model deployment [14].

After the data passes through pre-processing, it is continued at the input stage of the human face image, then the extraction of important features on the face and normalization of the feature vector which will then be classified according to the facial expressions that have been labeled on the datasheet to identify human emotions based on the trained model [15].

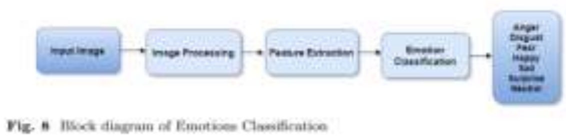

Fig. 9. Face recognition workflow

In the training and validation stage, the datasheet will be divided into two, namely the training set and the testing set to test the model.

3. RESULT AND DISCUSSION

The CNN model will be compared against the CNN+Haar Cascade and CNN+LBP models to find out the best performing model on the FER 2013 dataset.

3.1 CNN

The system consists of transmitter and receiver parts. The components in the transmitter system consist of sensors, GPS, microcontroller and telemetry module. Figure 3 shows the block diagram of the transmitter system.

- In Sarvakar et al. CNN was used to classify five major facial expressions with a two-part process, image background removal and facial expressive vector detection. The model was trained with the FER-2013 dataset consisting of approximately 35,000 images. The model was trained using 80% of the data and tested with 20% of the data. The model then predicts the emotion in the image based on the training that has been performed previously [3].
- Pranav, E et al. using Adam optimization algorithm to CNN by using 5 parameters of facial expressions in the dataset and got an accuracy rate of 78.04% [16].

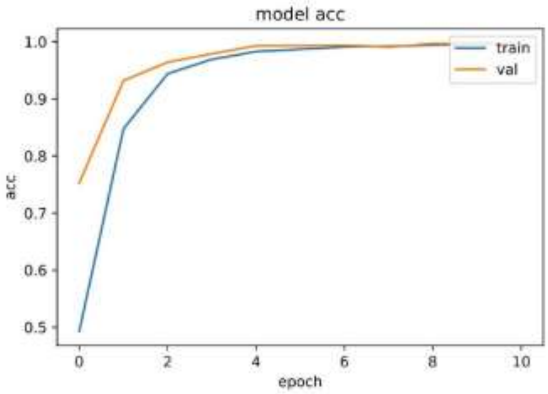

Fig. 9. Accuration rate with Adam optimizer

3.2 CNN+LBP

- Jumani et al. performed experiments using a combination of CNN and Local Binary patterns for face-based emotion identification using the FER2013 dataset with a training set of 28,709 images and a testing set of 3,589 images resulting in a training accuracy rate of 98% and 74% on testing [17]. The fig. (10) shows the accuracy rate on the testing and training sets.

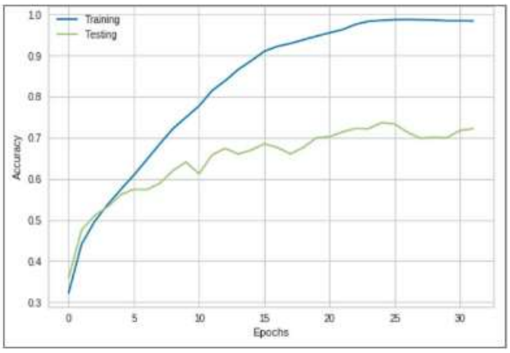

Fig. 10. Training and testing accuracy FER-LBPCNN

- Xu, Q et al. performed LBPCNN by expanding the dataset from FER 2013 with rotation variations up to 90 degrees giving a classification rate of 94.73% on seven facial expression parameters.[18]. Figure 11 shows that the results are higher than conventional models of CNN such as AlexNet (64.29%) and EmotionNet (66.71%) with the same dataset treatment.

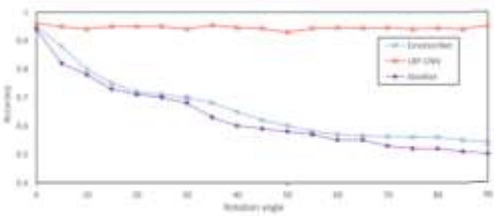

Fig. 11. LBCNN performance

3.3 CNN+Haar Cascade

- The integrated method between Haar Cascade and CNN works by dividing into training stage and testing stage. Haar cascade performs face segmentation and trains the CNN model to detect human emotions in the training stage and in the testing stage [19].

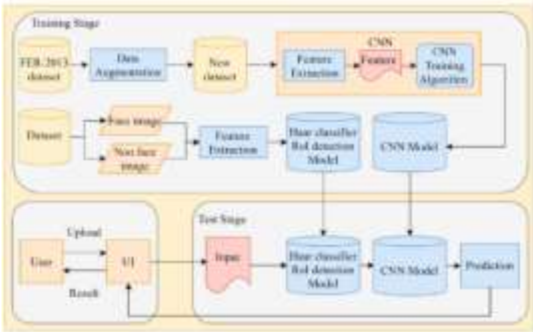

Fig. 12. CNN-Haar Cascaade mechanism

- Rasheed et al. Combined the Haar Cascade classifier and CNN methods by obtaining a validation performance accuracy of 65.59%, with a training time of about 87 seconds per epoch [15].

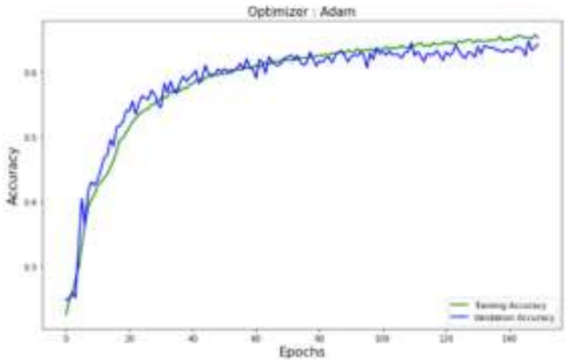

Fig. 13.CNN-Haar Cascaade accuracy rate

- Yeh et al.tested LBPCNN with FER2013 dataset using augmentation method Horizontal flipping and color adjustment on the dataset obtained accuracy rate of 68.36% and 64.34% respectively. This system has been tried to detect 75 different people and get 73.53% accuracy results and be able to correctly identify the emotions of 57 people with an accuracy rate of 55.8% [20].

4. CONCLUSION

Facial expression recognition is a complex and challenging task in the field of machine learning. Many methods and techniques have been developed to obtain good accuracy in this recognition task. A combination of LBP CNN, Haar Cascade CNN, and conventional CNN is discussed and gives various output accuracies. The treatment of the FER-2013 dataset is also affected in the accuracy validation outcome. From all the reviews, it is found that convolutional neural networks are used as the basic foundation for the development of emotion recognition through facial expressions as it provides high accuracy.

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Predictive Maintenance for Automatic Weather Station (AWS) Based on Anomaly Detection Using Autoencoder: A Literature Review

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A B S T R A C T

Automatic Weather Station or AWS is an instrument for measuring weather parameters automatically. The results of measuring weather parameters are very useful in the fields of meteorology and climatology, such as weather prediction, aviation and climate change. Especially in Indonesia, the Meteorology, Climatology and Geophysics Agency or BMKG has main tasks and functions in this field. Currently, data with accurate results is needed to produce accurate weather and climate predictions. However, sometimes there are anomalies in the data caused by AWS damage, resulting in inaccurate data. This will have an impact on modeling results in the fields of meteorology and climatology, where the modeling results are less precise. To overcome this problem, predictive maintenance is needed to avoid data errors in AWS operations. This research aims to build predictive maintenance at an Automatic Weather Station Based on Anomaly Detection using a Machine Learning Autoencoder. The anomaly data can be detected by machine learning autoencoders for monitoring AWS performance and conditions, that methodology applied in this study for build predictive maintenance in AWS. Finally, the expectation of this research is to make accurate predictive maintenance on AWS so perhaps that can reduce maintenance costs and increase the lifespan of the instrument before it breaks.

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1. INTRODUCTION

Automatic Weather Station or AWS is an automatic instrument system for measuring weather parameters in real time. The World Meteorology Organization (WMO) has defined an AWS as a meteorological station where weather parameters observations are automatically taken and sent. The amount of surface atmospheric observations are increased by using AWS and accuracy higher than using by manually [1]. One of the organizations that manages the field of meteorology and climatology in Indonesia is the Meteorology, Climatology and Geophysics Agency or BMKG.

Currently we have entered the industrial era 5.0. In industrial era 5.0, people and robots make a collaboration and disregard a competition in the future [2]. The appearance of rapidly expanding digital technology and artificial intelligence (AI)-based solutions is causing a rapid transition in the manufacturing sector today. The main issue for manufacturers worldwide is to increase production while still holding human involvement in manufacturing sectors [3]. The application of machine learning autoencoders for predictive maintenance is one example of implementation of artificial intelligence (AI) in contemporary society.

The goal and aim of predictive maintenance (PdM), that is the improvement of maintenance by a variation of preventive maintenance, is to extend the life and quality of equipment in AWS and guarantee sustainable operational management while enhancing the manufacturing process's performance and efficiency. By providing or enabling the opportunity for interventions through failure prediction, this recommended for decreasing probability in downtime, failures, and the frequency of stops without control, together with a reduction in service, maintaining, and fixing them expenses [4]. predictive maintenance as repairing methods are designed to assist meteorological instrumentation sectors according to their needs and help in maintenance requirements, as was discussed in earlier sections. AWS is one of them. Depending on the extent and improvement of technological and digital technology, various PdM model types may be available and can be used [5]. A machine learning autoencoder is one of the models utilized in predictive maintenance based on anomaly detection.

An example of a type unsupervised learning algorithm is the autoencoder, a kind of neural network that does not need data labelling. Learning a data entry to rearrange the data to a fewer-dimensional output is the goal [6]. In this research, the autoencoder uses anomaly detection data to make predictive maintenance.

Finding anomalies is a significant and serious problem that has been researched for a long time currently. For various applications and implementations, a wide variety of unique techniques have been created and applied to identify abnormalities. The challenge of identifying data patterns that deviate from expected behaviour will be applied [7]. An anomaly in the output data indicates an error in measurement caused by equipment damage.

In order to extend and increase the lifespan of AWS and save spending high costs in repairing when damage occurs, the goal of this project is to develop an accurate predictive maintenance system based on anomaly detection data on AWS.

2. METHODOLOGY

2.1 Data dan Data Sources

The dataset used is data from observations of weather parameters using AWS at the BMKG Class 1 Banjarbaru Climatology Station. The data-based technique or method known as Predictive Maintenance (PdM) has become a key area of research or study among the many other maintenance systems currently in use and applied. it increases a system's reliability by modeling system behavior, identifying trends, and anticipating breakdowns and failure through the use of statistical analysis, Machine Learning (ML) models, and Deep Learning (DL) solutions [8]: Model-based prognosis, knowledge-based prognosis, and data-driven prognosis are the three primary categories into which PdM techniques or method belong. In both industry and academia, data-driven PdM tactics have attracted major attention and significance [9]. The dataset is divided into 3, namely normal data, gradual failure data and immediate failure data. Each data contains the results of measurements of weather parameters including temperature, pressure, rainfall, sunlight and wind.

2.2 System Design Method

Fig. 1 below shows an example of a visualization of an autoencoder architecture. Applications such as dimensionality reduction, signal reconstruction, and anomaly detection have made complicated use of autoencoders [10].

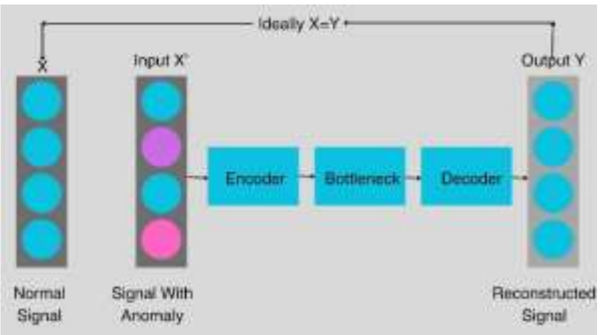

Fig. 1. Visualization of an autoencoder architecture [10]

The Explanation of illustration of autoencoder architecture. The network simplifies the input data into a smaller hidden modelling in the encoder section. it interventions or strategy to collect the most significant aspects of the data being collected. The original data is reconstructed from the encoder's hidden representation in the decoder's section. It attempts to generate and produce the supplied data as precisely as it can.

The network efficiently learns to filter out noise and irrelevant information during the learning phase by lowering variance between the input and reconstructed output or result.

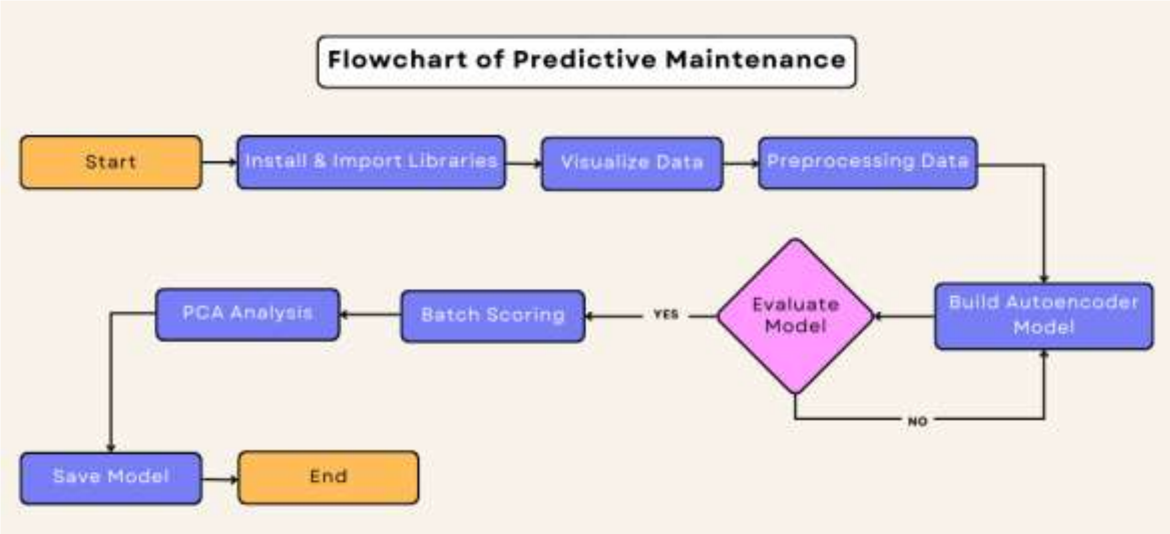

Fig. 2 Flowchart of predictive maintenance.

This the explanation about the step of flowchart that describes the predictive maintenance for AWS process using an autoencoder:

- Start: The initial stage of this process is predictive maintenance for AWS.
- Install & Import Libraries: Installed and imported necessary libraries for data analysis in predictive maintenance for AWS that are useful in predictive maintenance, such as pandas, tensorflow, and matplotlib.
- Visualize Data: Analyze data by creating visualizations to understand patterns, distribution, and outliers in the data.
- Preprocessing Data: Regulate the data to be normalized and divide it into testing and training data sets so that it is prepared and ready for use in model training.
- Build Autoencoder Model: Build autoencoder models using frameworks like Keras. This model will be used to detect anomalies.
- Evaluate Model: Test and evaluate model performance using appropriate metrics, such as Mean Squared Error (MSE).
- Batch Scoring: Perform batch scoring on test data to detect anomalies based on the trained model.
- PCA Analysis: Carrying out PCA (Principal Component Analysis) analysis to reduce data dimensions and visualize scoring results.
- Save Model: For later usage, archive the scalar and trained model.
- End: The final stage of the process, indicating that all steps have been completed predictive maintenance for AWS.

2.3 Program Tool

In this research, the tool used is Google Collab as a tool for executing predictive maintenance for AWS. To transport out the entire experiment using a dataset, Google collab is utilized [11].

2.4 Programming

In this research, the author uses Python as a programming language to create predictive maintenance for AWS. while the machine learning used is a machine learning autoencoder. The modeling and execution is done in Google Collab.

3. LITERATURE REVIEW

3.1 Predictive Maintenance

In the industrial and meteorological instrument sector, maintenance is crucial and vital because it can provide explanations for an important percentage of a company's or agency operating costs [12]. Today, where technological developments grow faster, maintenance efficiency is needed to avoid more serious equipment or instrument damage. One of the solutions is through predictive maintenance. Condition-Based Maintenance (CMB) delivered rise to more advanced and successful methods or techniques, like predictive maintenance

(PdM), which combines capabilities in automation, engineering information technology, and data analytics with the concepts of IoT and Cyber Physical System (CPS) [12].

Predictive maintenance has been applied in some industries to efficiency cost. For example, Ref. [16] Apply deep learning methods to avoid Metro do Porto Trains Air Production Unit (APU) technology from malfunctioning. They were also able to increase the accuracy of failure estimations, which results in higher-quality maintenance. To prevent or avoid inaccurate data in the necessary continuous anticipation and accuracy, however, they have to upgrade the sensor. Reference [17] used predictive maintenance to overcome traditional maintenance strategies either risk machine downtime or replace parts prematurely, leading to financial losses and inefficiencies. This also has similar results with [18] being successful in reducing unplanned downtime. Hopely in the future they can require extensive data for training to produce accurate results. To effectively manage the high number of vehicle data, Theissler et al. [19] applied machine learning (ML)-enabled predictive maintenance. From several researchers, they have demonstrated the effectiveness of predictive maintenance for efficiency and reducing instrumentation failure.

Reference [41] builds predictive maintenance by applying a set-based design method by using a physical model of the equipment to identify and mitigate potential failures or downtime. Reference [42] to reconstructed corrupted signals and reduce maintenance downtime, so they design a predictive maintenance system using computational fluid dynamics (CFD) to get operational efficiency of the HH-60G Helicopter. The improvement of predictive maintenance by integration of data analytic and AI has demonstrated by [43]. Similar to [44], they make expansion to emerging technologies in development of predictive maintenance. Reference [45] applied predictive maintenance in the Dry 8 Production machine line by implementing the Support Vector Machine (SVM) to reduce downtime or failure and also effectively increase productivity.

From the statement above, that can conclude if researchers have made some improvement in predictive maintenance. In this paper, the author wants to make an improvement to the Automatic weather Station (AWS).

3.2 Anomaly Detection

Determining data values that significantly disappear from the expected pattern is the focus of anomaly detection. A number of variables could be dependable for the anomaly, like malfunctioning sensors, low batteries, or data transmission errors; other factors could be industrial equipment or sensors if it results in AWS failures, or events, like production line changes or curative arrests. Anomalies produced by incidents in the machinery present the analyzer with accurate details, whereas anomalies caused by sensor weaknesses lack and could result in data to be misinterpreted. These anomalies could be classified as noise, however as previously stated, the process by which anomalies and noise are explained varies depending on the kind of data [13].

Anomaly detection has been used in some research. For example, Anomaly detection has been applied to predictive maintenance (PdM) models in industrial settings in Ref. [15]. They used data from rolling mills in the steel sector to show data that was abnormal. Similar to [16] created a predictive maintenance using framework for one of the machines in railways, the air production unit (APU) that operates Metro do Porto trains using anomaly detection. Reference [17] improves predictive maintenance by accurately detecting anomalies using data from industrial equipment. So they can improve asset health and performance. Ref. [18] used anomaly detection by time-series sensor data from an electrical rotary machine, including normal and fault data. This data needed to identify anomalies knowing the difference of normal and fault data. Similar to [20] employed SpectraQuest's Machinery that has an event Trouble Simulator to detect deviations in time series data from sensors, including healthy and abnormal states. Also, Fathi *et al.* [23] employed time-series using data from a three-dimensional Department of Fisheries delta robot conducting pick process-and-place tasks to find anomalies. Karapalidou *et al.* [25] used anomaly detection by multivariate time series data from industrial blower ball bearing units. Breux *et al.* [26] used anomaly detection by Sensor data from a data center's UPS system collected between January 2019 and May 2021. Roelofes *et al.* [27] used anomaly detection by wind turbine sensor data, including an open dataset with artificially added errors for controlled testing. Ref. [28] utilized SpectraQuest's gearbox fault-diagnostics simulator to detect anomalies in gearbox vibration data, including both broken-tooth and healthy states. Ref. [29] Using historical information from a KUKA, which is a KR6R 900 SIXX robot for manufacturing to find anomalies. Ref. [30] Utilized anomaly detection by acceleration data collected from sensors during container handling operations. Overall researchers have used anomaly detection to label data and use it in prediction. They also use health data to identify deviations.

3.3 Automatic Weather Station (AWS)

AWSs (automated weather stations) are widely used to collect climate and meteorological data. Guidelines for the deployment, setup, and operation of these stations are published by the World Meteorological Organization (WMO) [14]. There are four (4) types of AWS, according to WMO:

a. Use light AWS to measure a few variables, such as air temperature and/or precipitation. The only limitations of this AWS are in air and rainfall measurements.

b. Simple AWS for measuring the fundamental meteorological parameters (atmospheric pressure, precipitation, wind direction and speed, air temperature, and relative humidity). Meteorology typically makes use of this AWS.
c. Extended AWS measures evaporation, soil temperature, sunshine duration, and solar radiation. This enhances AWS, which is typically utilized in climatology.
d. AWS that automate visual observations (current weather and cloud base height). All of the categories offer the option to transfer data using a range of techniques and to log data utilizing a proprietary data logger [1].

AWS is usually implemented to measure weather parameters. Some research has been built on AWS with some improvement. For example, Ref. [31] To improve and develop learning, create and execute an instructional model of an Internet of Things weather station that makes use of cloud services. The weather station is incorporated into the Internet of Things (IoT) and effectively measures environmental characteristics such as temperature, humidity, and pressure. But, this research needs improvement so the weather station can be used for outdoor conditions. Similar to [32] design weather station device that measures both weather conditions and air quality using IoT technology. The researcher improved air quality measurement. Reference [33] the development of AWS and Precision Grid Meteorological Information System (PGMIS) enhances the accuracy and timeliness of meteorological data, contributing to better disaster management and energy use. The improvement of IoT and sensors help AWS to produce data with high accuracy and precision. However, manually still needed to complete the data, like [34] confirm that data from Automatic Weather Stations (AWSs) is of comparable quality to manually observed data and can bridge data gaps. For more information about research in AWS, Ioannoue *et al.* [1] Examine and investigate the methods and technology utilized to implement Automatic operation Weather Stations (AWS), especially in relation to the Internet of Things (IoT).

Reference [35] makes an improvement of AWS using Artificial Neural Network (ANN) to detect sensor errors so that it can increase a number of accuracy data. Reference [36] developed a website called Automatic Weather Station Data Tool (ADT) using integrated data from various AWS networks that can assist National Meteorological Services (NMS) access, process, perform quality control and visualize data from different AWS networks in one place. Some researchers also build and design AWS with low cost for meteorological upper observation, that implemented by [37]. Reference [38] design AWS using microcontroller and weather forecasting device as based. This has advantages in techno economics and meteorological data collection. But, continuous maintenance is needed. The integration of AWS with IoT has been implemented by [39], the researcher designed an AWS with intelligence based on Internet of Things (IoT) to improve data accuracy and real time monitoring. The last, Ref. [40] design Automatic Weather Station with low cost and also based DIY in IoT to result in accurate and real time weather data.

Conclusion, AWS has been built with some improvement technology and also to complete manually data observation. But, they have not improved in maintenance. So, in the next research, perhaps the author can develop predictive maintenance in AWS.

3.4 Autoencoder

Autoencoder is classified as unsupervised type, where anomaly detection techniques aim to find abnormalities based on the inherent structure of data and lack labeled data. This algorithm has the advantage that it can learn complex, non-linear relationships, Robust to noise with denoising and variational variants. But this also has disadvantages, where requiring large amounts of training data can be computationally expensive [22].

Some studies related to problems in the below information that can be solved using machine learning autoencoders. Autoencoders have been used in some research. For example, Ref. [15] used Variational Autoencoder (VAE) for unsupervised anomaly detection and SHapley Additive exPlanations (SHAP) for model explainability. This need requires further validation and optimization for improvement. Ref. [16] implemented a Sparse Autoencoder (SAE) network to detect anomalies. Beneficially this is reduced false alarms and enhanced maintenance planning. Ref. [17] suggests a brand-new deep learning method for anomaly identification in predictive maintenance that combines Automatic encoders and LSTM (Long Short Term Memory) models. By precisely identifying anomalies, this combined approach can result in predictive maintenance. Ref. [18] utilizes stacked autoencoders (SAEs) to model normal machine behavior and detect anomalies. This enables early fault detection and intervention in industrial motors.

Another research also can be our references. Like, Ref. [21] without the need for domain-specific physics knowledge, machine learning with Autoencoders (AE) is used to forecast the current-voltage (IV) and capacitance-voltage (also known as CV) curves of FinFET transistors. This study improves the efficiency of semiconductor devices. Ref. [20] Comparison between a regular autoencoder and an LSTM-autoencoder model, focusing on MSE deviations, training duration, and decline function for anomaly detection in Electric Motors. The result is that the LSTM-autoencoder model is better than regular autoencoder. Although slower because of the intricacy of the LSTM layers, the LSTM-autoencoder displayed significantly lower loss values and MSE anomalies than the standard autoencoder. Ref. [23] using autoencoders (AEs) for anomaly detection and maintenance prediction in a 3 DoF delta robot, even without Run-to-Failure (R2F) data. This has advantages in simple data because no need for R2F data. But, this affects the accuracy and complexity of data. Ref. [24] using PredMax, a predictive maintenance tool that combines the use of principal component analysis (PCA) along with deep convolutional neural networks autoencoders (DCAE) for data grouping and dimensionality reduction. All things considered, this effectively located the most delicate machine components and times of unusual operation in an industrial gearbox case study. Ref. [25] using multivariate time-series information of industrial blower ball bearing units, an organized sparse LSTM Autoencoder is trained on typical operational data to identify anomalies. This is effective in anomaly detection but still requires extensive data preprocessing and computational resources for improvement. Ref. [26] uses multiple autoencoders, each for a different sensor, to reconstruct inputs and detect anomalies with a random forest classifier in a data center. F1-score of this method achieved 83.60% that showed the balancing of precision and recall that has relation in high accuracy. Ref. [27] use autoencoders for anomaly detection and ARCANA for root cause analysis by optimizing reconstruction errors to highlight significant features. The result, ARCANA successfully identified the wind speed sensor as the root cause of anomalies with higher accuracy than traditional methods. Ref. [28] a deep learning framework for industrial machine anomaly detection and fault investigation based on a six-layer autoencoder. The proposed model achieved an overall accuracy of 91%. That showed the high accuracy. But, that still has potential overfitting and the need for further validation with different industrial data sets. Ref. [29] identifying irregularities in robot activities using the SWCVAE model. The suggested model proved useful for condition-based maintenance since it was able to identify abnormalities in the robot. This has the advantages in effective real time detection. Ref. [30] to find irregularities in the acceleration data, an auto-encoder model was employed. The auto-encoder successfully detected critical impacts, showing improved speed and accuracy over IDM. Depending on the container sway axis, it detected anything from nine to eighteen impacts. In a lab setting, the system was evaluated and contrasted with the Impacts Detection Methodology (IDM). Perhaps in future, this research needs improvement on Requires proper programming and testing in various real-life scenarios for high accuracy and any conditions.

Several researchers have demonstrated that autoencoders are highly effective in anomaly detection. In this research, the author wants to use autoencoders to design predictive maintenance in AWS.

4. CONCLUSION

In order to improve the efficiency of AWS maintenance, the primary goal of this article is to build predictive maintenance for AWS based on identifying anomalies utilizing artificial intelligence autoencoders that can speed up the predictive maintenance flow. To be able to design the desired predictive maintenance, the machine learning autoencoder is used. Anomaly detection is used to predict AWS before failure. This research will be designed in Google collab, which is easy using applications and simple features. The main objective of this study is to create predictive maintenance for Automatic Weather Station (AWS) to avoid the failure of instrumentation.

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The Utilization of IoT in Real-time Temperature and Humidity Monitoring Using Microcontroller: A Literature Review

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A B S T R A C T

Temperature and humidity must be considered in various fields such as weather, agriculture, technology and industry. The Internet of Things (IoT) can be applied in temperature and humidity monitoring systems so that the data obtained is real time. The research uses a literature review method that has the main goal of searching journals through Google Scholar. This study analyzes the use of IoT for temperature and humidity monitoring using various sensors such as DHT22, DHT11, and DS18B20 in various fields. Based on several journals from 2017 to 2024, it was selected to provide an understanding of the effectiveness and accuracy of different types of sensors in environmental monitoring. The results of the study show that IOT makes it easier to monitor environmental conditions efficiently and accurately, helping to make decisions quickly and automatically. The DHT22 sensor is effective for monitoring due to its low cost and good quality, while DS18B20 excels in accuracy. This research is useful in the development of IoT in various environmental monitoring needs.

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1. INTRODUCTION

Observation of temperature and humidity values is an important aspect in various fields, such as weather, agriculture, technology, and industry. The values on these two parameters affect quality, safety, and the environment. Consistent measurement and monitoring of these two parameters can help ensure environmental conditions are within the optimal range of the observed area. So that to improve the operational efficiency of a system, it is necessary to maintain product quality. This research aims to develop accurate temperature and humidity monitoring methods to support the stability of various aspects of life. It is hoped that with this research, problems caused by temperature and humidity conditions will not occur again so that no losses will occur.

This can be exemplified in the agricultural sector where the type of plants planted must be adjusted to the temperature conditions and also the soil in the area. Like tea plants are

better in the mountains and corn is better in the lowlands. In the field of Technology, it can be seen that electronic devices are very vulnerable to high temperatures so that they will cause wars to be damaged faster. Meanwhile, in industrial factors, it can be exemplified in the food industry for the storage of ingredients, temperature and humidity conditions must be considered so that the ingredients are not damaged.

In this modern era where technology is increasingly developing and making human life inseparable from technology. The Internet of Things (IoT) can be used in various fields, including monitoring environmental conditions. IoT can allow users to control sensor data anywhere in real-time. With IoT, devices like the Arduino UNO can collect data and transmit it through a Wi-Fi module and allow us to know and analyze data remotely [1]. Internet of Things (IoT) platforms can be used to analyze temperature and humidity data. If only using a space thermometer to monitor environmental data with a small observation area, it is not enough. This is evidenced by the statement that temperature and humidity vary greatly in various locations. Conditions that exist in different regions can be very different [2].

DHT22 sensors and similar types are mostly used in IoT temperature and humidity monitoring systems, however, there is limited information about validating the accuracy of DHT22 sensors [3]. By utilizing sensors connected to the network, the system can automatically transmit data to a monitoring platform that can be accessed remotely. IoT-based temperature and humidity monitoring systems also support tool automation, such as controlling fans, heaters, or cooling systems based on observed environmental conditions. This is useful for improving energy efficiency and reducing operational costs. Automation of this equipment is very important to do in this day and age where humans want something in an easy way.

2. RESEARCH METHOD

2.1 Data Sources and Search Strategies

This study uses a literature review method that has the main purpose of searching journals through Google Scholar. In the search process, it is focused on the title of the Journal with appropriate keywords such as the words "IoT", "temperature", and "humidity". After that, a search was carried out about the theme. The selected journal is an English-language journal published in the 2017 - 2024 times frame [4].

2.2 Inclusion Criteria

In writing this journal, certain criteria are used where the journal must use sensors to measure temperature and humidity such as DHT11, DHT22, or DS18B20 and must use IoT. Journals that only use sensors and are not integrated with IoT are not used.

2.3 Quality Assesment

This study does not use a standard that is usually used to assess the results of IoT-based research for temperature and humidity observation. Thus, the risk of bias is evaluated on two main assessments, namely the accuracy of sensor measurements and reliability in transmitting data and humidity observation. Thus, the risk of bias is evaluated on two main assessments, namely the accuracy of sensor measurements and reliability in transmitting data.

3. RESULT AND DISCUSSION

Table 1. Literature Review Result

No	Title	Year	Author	Remarks
1	Design of Monitoring System Temperature And Humidity Using DHT22 Sensor and NRF24L01 Based on Arduino	2023	Azhari Nasution, T. I. Sinaga, S. H. Sudiati	The research begins with a literature study, followed by system design based on hardware and software requirements. This system uses of a base node (Arduino Uno, nRF24L01) and a client node (Arduino-Uno, DHT22, LDR, nRF24L01). Data is collected and transmitted wirelessly, with real-time results displayed on an LCD. A buzzer alarm triggers if the temperature exceeds 32°C or humidity exceeds 65%. The power supply uses a step-down transformer to convert 220V AC to 12V DC. The NRF24L01 module provides reliable communication over 800 meters, with sensor accuracy of 1.4% for temperature and 3.8% for humidity.
2	On the Evaluation of DHT22 Temperature Sensor for IoT Application	2021	Ahmad, Yasser Asrul Surya Gunawan, Teddy Mansor, Hasmah Hamida, Belal Ahmed Fikri Hishamudin, Adam Arifin, Fatchul	The temperature monitoring system uses a DHT22 sensor and is connected to a Raspberry-Pi, MySQL database, and Grafana for real-time display. The DHT22 was chosen for its accuracy, affordability, and low power consumption. The system was compared to an industrial-grade Keithley 6517-TP thermocouple across three experiments: room temperature, ice bath, and boiling water. While the DHT22 provided accurate readings, it was slower in detecting rapid temperature changes. The system is ideal for monitoring environments with gradual temperature shifts due to its low cost and IoT capabilities.
3	IoT based Temperature and Humidity Controlling using Arduino and Raspberry Pi	2019	Barik, Lalbihari	IoT-based systems for temperature and humidity detection are an efficient way to monitor farm conditions in real time. The sensors will continuously measure these parameters, and the data is sent to a

				cloud platform via an Arduino microcontroller, and the information is then sent to the farmers' mobile phones via GSM, allowing them to track environmental conditions remotely. This system helps farmers make timely decisions to optimize crop growth and can prevent problems such as overwatering or drought. The setup is energy-efficient, cost-effective, and scalable for a wider range of agricultural applications.
4	Performance Analysis Comparison of DHT11, DHT22 and DS18B20 as Temperature Measurement	2023	Yulizar, David Soekirno, Santoso Ananda, Naufal Prabowo, Muhammad Agung Perdana, Ilham Fajar Putra Aofany, Diar	Temperature monitoring is essential in various sectors such as agriculture, food production, and healthcare, making temperature monitoring essential. Temperature sensors are commonly used in applications such as seawater desalination, hydroponics, and fermentation processes. This study compares the accuracy of three temperature sensors: DHT11, DHT22, and DS18B20. Laboratory calibration and field tests were conducted. The results showed that DS18B20 had the smallest uncertainty (0.17°C) and the highest accuracy (99.05%), followed by DHT22 (98.15%) and DHT11 (97.19%). Thus, DS18B20 is more accurate and reliable for temperature measurement.
5	The feasibility study: Accuracy and precision of DHT 22 in measuring the temperature and humidity in the greenhouse	2023	Wardani, I. K. Ichniarsyah, A. N. Telaumbanua, M. Priyonggo, B. Fil'Aini, R. Mufidah, Z. Dewangga, D. A.	This greenhouse uses hydroponic systems like the nutrient film technique and Dutch bucket to grow high-value crops like lettuce, pak choi, and melon. The study aimed to create a microclimate monitoring system for the greenhouse using affordable sensors. DHT22 sensors were used to measure temperature and humidity at different points in the greenhouse, transmitting data through a master-slave system based on Atmega2560 and ESP32. The system sends real-time data to a cloud platform, Ubidots, accessible via mobile devices. The study found that the DHT22 sensors provided accurate readings, with RMSE values of 1.48°C for temperature and 3.18% for humidity. Regression analysis showed strong correlation coefficients, indicating the system's precision in monitoring greenhouse conditions. The research contributes to affordable smart farming technologies for Indonesia.
6	Server Room Temperature & Humidity Monitoring Based on Internet of Thing (IoT)	2019	Alvan Prastoyo Utomo, Moechammad Aziz, Abdul Winarno Harjito, Bambang	An IoT-based temperature and humidity monitoring system is quite effective in monitoring and controlling conditions in the server room. The DHT22 sensor used can detect changes in temperature and humidity with good accuracy. The data collected in real-time is stored on the server and can be accessed via the web and notifications are sent to the user via the Telegram application if the temperature or humidity exceeds a pre-defined limit. This system allows users to control the temperature of the server room remotely, improving efficiency and preventing hardware damage in the event of drastic environmental changes.
7	Monitoring and Control Food Temperature and Humidity using Internet of Things Based-on Microcontroller	2021	Riadi, Imam Syaefudin, Rizal	The system is designed into two things: hardware and software for data transmission. DHT22 is used to measure temperature and humidity, and the data is sent to a server using ESP8266. If humidity exceeds 80%, a heater is activated; if temperature exceeds 30°C, a cooler is turned on. Results and Discussion The system has been tested for temperature and humidity control, with results indicating that the DHT22 provides accurate data. Temperature control tests showed fluctuations that aligned with the settings, while humidity tests indicated a decrease in humidity values as expected. Data was transmitted and visualized through the Thingspeak application, indicating

				successful data transmission. Fermentation of tempeh lasts about 2-3 days with an optimal temperature of 35°C. Data analysis was performed using standard deviations to evaluate sensor accuracy, revealing that small deviation standards show accurate and representative data.
8	Distant temperature and humidity monitoring: prediction and measurement	2021	Hafeez, Farrukh Sheikh, Usman Ullah Khidrani, Attaullah Bhayo, Muhammad Akram Abdallah Altbawi, Saleh Masoud Jumani, Touqeer Ahmed	Over the past decade, manufactured insights (AI) has significantly affected areas such as dialect preparing, healthcare, and observation. Machine learning calculations analyze designs, driving to developments like self-driving cars and progressed climate estimating. The Web of Things (IoT) is additionally progressing quickly, with applications in savvy homes and horticulture, making IoT more progressive than the mechanical transformation due to broad smartphone utilize. This paper presents a show for monitoring humidity and temperature employing a Wi-Fi-connected mechanical vehicle. It utilizes a repetitive neural organize (RNN) with a DHT22 sensor for estimations and an IP camera for route. Comes about demonstrate tall forecast precision, improving unwavering quality for future work including progressed calculations and broad information collection.
9	Monitoring Temperature, Humidity And Controlling System In Industrial Fixed Room Storage Based On Iot	2020	Seman, Mohd Tarmizi Abdullah, M. N. Ishak, M. K.	By using several techniques in its processing, it is hoped that it can compare the measured value and the expected value in one study. Data-driven machine learning algorithms aim to predict values from temperature and humidity. The experiment was conducted in both outdoor and indoor environments. The statistical results reveal that, compared to outdoor settings, indoor environments achieve higher accuracy. To further improve the accuracy of the model, more data must be collected over a longer period of time. In addition, better meteorology-related algorithms can be used to get more accurate predictions. The use of special and advanced temperature and humidity sensors will also increase the accuracy value
10	Modeling Automatic Room Temperature and Humidity Monitoring System with Fan Control on the Internet of Things	2022	Hendajani, Fivtatianti Mughni, Arif Wardhani, Ire Puspa Hakim, Abdul	This IoT-based system has two main functions: monitoring temperature and humidity using the DHT22 sensor displayed on the web page, and controlling fan speed with pulse width modulation. (PWM). The fan is operated manually, but it can be automated based on the room's temperature and humidity values. This system uses the L298N motor driver and requires an additional power supply for the fan. The website can be accessed using the server's IP address, and it is recommended to add a password for security. This prototype can be developed for various electronic devices such as fans, lights, and TVs. The use of applications like Blynk is recommended for global access and further development.
11	Development of embedded system in monitoring temperature and humidity as supporting smart farm	2020	Puspasari, Fitri Fahrurrozi, Imam Oktiawati, Unan Yusmaniar Satya, Trias Prima	NodeMCUs can be integrated with temperature and humidity sensors and their outputs can be transmitted over the web in realtime. Temperature and humidity data is sent from the NodeMCU device to a database, which is then viewed on the website. In the future, this gadget can be equipped by installing it on a fan or a locked blower. So that the microcontroller can directly instruct the blower to lower the temperature of the cage when it reaches the comfort zone. Significant advances in information and communication technology have improved traditional monitoring and mitigation methods in terms of precision and accuracy

				and faster delivery of measurement results, enabling savings in cost, time, and energy.
12	Temperature and Humidity Monitoring System in Internet of Things-based Solar Dryer Dome	2023	Tazakka Ma'arij, Dzakarasma Yudhana, Anton Ma'arij, D T Yudhana, A	The study shows that weather, temperature, and humidity are correlated. During the day, the temperature and humidity inside the SDD are higher and lower than those outside, regardless of whether it is raining or clear. The temperature error values for the DHT22 and DHT11 sensors, compared to the ThermoPro, are 1.572% and 0.721%, respectively. However, the humidity error values differ, with both DHT22 and DHT11 showing a 5% inaccuracy compared to the ThermoPro. This indicates that adjustments are needed in the program. The greatest temperature difference between the inside and outside of the SDD occurs at 9:00 AM WIB.
13	A Prototype of Monitoring Temperature and Humidity on Photovoltaic Using ESP8266	2020	Subastiyan, H. Sunanda, W. Gusa, R. F.	In the province of the Bangka Belitung Islands, the need for power has been rising yearly. According to the most recent data, the region has 77,362 kVA of connected capacity, 449,450 consumers, and an installed power capacity of 353.9 MW. Steam, diesel, biomass, and gas plants are among the power sources; their combined capacity is 306 MW, and their net output is 280 MW. As a result, solar energy is being investigated as a potential alternative energy source, especially on the island. Using sensors to gather data on temperature, humidity, sun radiation, and voltage for analysis, this study focuses on monitoring photovoltaic parameters.
14	Designing an IoT system for monitoring and controlling temperature and humidity in mushroom cultivation fields	2019	Nasution, Tigor Hamonangan Yasir, Muhammad Fahmi Soeharwinto	an IoT-based monitoring system successfully measured temperature and humidity for oyster mushroom cultivation. Temperature and humidity are sent to the cloud using ThingSpeak once every 30 minutes. The system is also able to control the temperature of around 25-29°C to support the growth of mushrooms. The results of the experiment showed that oyster mushroom cultivation with a temperature control system was more effective, because optimal environmental conditions could be maintained. This shows the potential of IoT in improving efficiency for the agricultural sector.
15	Implementation Of Monitoring and Control Temperature and HumidityBased on IoT in The Oyster Mushroom Cultivation Room	2023	Wibowo, Budi Cahyo Rozaq, Imam Abdul Pratama, Tredi Pratama	Experiments conducted by the author, it was found that the DHT22 sensor has an accuracy level of 99.44% for temperature measurement and 99.4% for humidity. The website will instruct the existing actuator with a delay of 2.8 s to heat up and 3 s to pump. This is used to maintain the temperature and humidity conditions of the kumbung chamber against the optimal temperature and humidity values that have been determined. For the average watering time is 115 s and for the heater 383 s.
16	Implementing IoT for Development of a Low-Cost Environmental Monitoring System	2018	Nascimento, Michel H.S. Moreira, Anderson L.S. Domingues, Marco A.O. Castro, Arthur L. Moura, Denis L.	The DHT22 sensor has quite good quality in temperature and humidity monitoring in systems integrated with IoT. DHT22 has a temperature range between -40°C to +80°C with quite good accuracy and a humidity range from 0 to 100% RH (Relative Humidity). In addition, this sensor also has low power consumption, making it suitable for IoT applications that operate continuously with a maximum consumption of 1.5mA. The DHT22 can provide measurement results in a digital format through data pins, making it easy to integrate into microcontrollers such as NodeMCUs used in IoT systems. Its advantage over other sensors is its ability to provide accurate data with little delay, although additional calibration may be required when used in extreme environments.

17	Development of Temperature and Humidity Control System in Internet-of-Things based Oyster Mushroom Cultivation	2020	Najmurrokhman, Asep Kusnandar Daelami, Ahmad Nurlina, Elin Komarudin, Udin Ridhatama, Hasbi	Monitoring and control of humidity and temperature are important factors for optimal oyster mushroom cultivation, where the conditions must be in the range of 18-30°C and humidity 65-85%. IoT-based systems, such as Cayenne, allow for real-time remote monitoring and maintenance, ensuring mold grows in the ideal environment. Sensors such as the DHT11 can monitor temperature and humidity data, so actuators such as fans and mistmakers can maintain conditions within the required limits. This increases efficiency by enabling continuous monitoring and automated adjustments, supporting high-quality mushroom production.
18	Development of an IoT-based Real-Time Temperature and Humidity Monitoring System for Factory Electrical Panel Rooms	2024	Medagedara, O. V. Liyanage, M. H.	The Arduino IDE's serial monitor shows the programmed algorithm and the IP address for accessing the web server online. This created IP address enables users to see a visual display of temperature and humidity readings that are refreshed every 30 seconds. Data is collected every 10 seconds using the DHT22 sensor to maintain server efficiency and guarantee smooth functioning. The configuration of the chart, such as axes, text alignment, colors, and component positioning, is set up through an HTML file that is sent to the microcontroller, guaranteeing a precise visual display of the gathered information.
19	IoT based temperature and humidity monitoring framework	2020	Rahman, Rafizah Ab Hashim, Ummi Rabaah Ahmad, Sabrina	IoT platforms can be used to analyze temperature and humidity data. If only using a space thermometer to monitor environmental data with a small observation area, it is not enough. This is evidenced by the statement that temperature and humidity vary greatly in various locations. Conditions that exist in different regions can be very different
20	Monitoring temperature and humidity of server room using Lattepanda and ThingSpeak	2019	Nasution, T. H. Muchtar, M. A. Seniman, S. Siregar, I.	IoT-based temperature and humidity monitoring systems, which use Lattepanda and ThingSpeak, can ensure optimal conditions in the server room. Monitoring is carried out in real-time every 30 seconds, allowing for more effective management of temperature and humidity to prevent potential damage that may occur. By utilizing the DHT11 sensor, temperature and humidity data can be sent in real-time and observed in the form of graphs through the ThingSpeak platform. This system can support data-driven decision-making for better infrastructure management.

Several scientific journals show that IoT technology plays a very important role in monitoring optimal agricultural environmental conditions. The DHT22 sensor, along with Arduino and NodeMCU, used for accurate temperature and humidity monitoring. The data helps farmers in managing agricultural conditions effectively to support optimal plant growth [5], [6]. By using data that can be monitored in real-time, farmers will be able to immediately find out the condition of the plants even though they are not in place. For example, a temperature and humidity monitoring system with IoT is applied in maintaining temperature and humidity for oyster mushroom cultivation rooms. Temperature and humidity are automatically controlled to ensure the ideal environment is expected to add to the value of productivity [7], [8]. It can also be applied in different types of fungi such as beetle mushrooms. The Cayenne app can also be used for real-time access options and remote monitoring [9].

Monitoring of temperature and humidity values is also important for microclimates in greenhouses. The DHT22 and DHT11-based systems used in the experiment provided results with high accuracy. The system can also be connected to a cloud platform so that it can be accessed in real-time [10], [11]. This can help greenhouse owners to know the condition of the greenhouse and can solve the problem quickly. In addition, by utilizing DHT22 sensors and RNN networks. Users can create a system to predict and measure temperature and humidity inside existing greenhouses. The system generates accurate predictions for the automatic setting of the greenhouse environment [12]. With this prediction system, if an extreme condition occurs, users can prepare preparations so that the quality of the greenhouse is maintained. To automatically maintain environmental conditions in agricultural greenhouses to match the desired conditions, fan control using PWM can be used [13].

In the industrial field, IoT systems can also be applied to monitor temperature and humidity for raw material storage rooms to be produced. The DHT22 sensor integrated with ESP8266 can be used to maintain material quality by automatically activating the temperature and humidity control device if the storage space conditions go out of the desired limits [14]. In addition to being monitored, a system can be equipped with tools that are used to restore temperature and humidity values according to the desired. If after the temperature and humidity control device is active, the user can still observe whether the condition is normal or not. And if it is still not normal within a certain period of time, users can come directly to check the condition of the room

For monitoring systems, Lattepanda and ThingSpeak can be used so that data visualized in the form of graphs[15], [16]. With graphs, the data will be easier to analyze. The use of IoT in industrial storage systems can also be used to compare environmental conditions inside and

outside industrial spaces. This aims for long-term monitoring that allows the development of algorithms for efficient environmental control of the industrial area [3]. IoT platforms can be used to analyze temperature and humidity data. If only using a space thermometer to monitor environmental data with a small observation area, it is not enough. This is evidenced by the statement that temperature and humidity vary greatly in various locations. The results of the statistics reveal that, compared to outdoor settings, indoor environments achieve higher accuracy [17].

The monitoring system can also be applied in the food industry by utilizing DHT22 to monitor temperature and humidity conditions in food fermentation chambers [13]. The IoT system developed is useful for supporting the automatic control of air conditioning and heating according to specified parameters [18]. This can improve the quality of fermented results because in making fermented food, the value of temperature and humidity in the room must be considered. This is because yeast or bacteria used for making fermented food have special conditions in order to develop properly. In addition, another acceptable advantage is the reduction of losses caused by the failure of the fermentation process on the material.

This system can also be implemented to monitor the temperature and humidity in the server room. By using DHT22 sensors and Telegram platform for real-time alerts. This system allows the adjustment of the temperature and humidity in the room to meet safe limits and avoid damage to the device [16]. Of course, this is very important because the price of existing devices is likely to have a high value. It is hoped that by using this system it is expected to be free from damage to the device due to poor room conditions. This can happen because if the temperature is too high, the device will also become hot. Then if the temperature is very cold, the humidity will be high so that the water content in the air is very high which can result in an electrical short circuit.

In solar panels, temperature, humidity, and voltage monitoring can be controlled using ESP8266. This system can be used to ensure that optimal conditions so that the energy efficiency of the panels can be well maintained, especially in areas with high solar radiation such as Bangka Belitung province [19]. This system can use DHT22 and can be set up with updates every 30 seconds to maintain operational stability in the factory [20]. This is very important to be able to utilize the power source that comes from sunlight. If the efficiency level of the tool is high, a large amount of energy will be obtained. However, if the efficiency of the equipment is low, the potential of areas with high solar radiation will not be optimal.

Sensor DS18B20 is the sensor with the highest accuracy for temperatures with an uncertainty of about 0.17°C, then for the DHT22 sensor with an accuracy of 98.15%. However, in its application, the DHT22 sensor is more often used because of its fairly good accuracy and lower cost. Although DS18B20 sensors provide the best results in applications that require highly precise measurements [21]. In this case, it can be understood that in making a tool, the economic factor of the tool to be designed must also be considered. The DHT22 sensor is of good quality for temperature and humidity monitoring with IoT systems, has a temperature range of -40°C to +80°C, humidity 0-100% RH, low power consumption, and accurate measurement capabilities, but may require additional calibration in extreme environments [22].

This can be a guide that in designing a system, you must not only pay attention to the value of accuracy. However, it must also pay attention to its economic value. If a system can have a low price and good enough accuracy, the device can be mass-made and make more existing observation locations. This is of course better because as explained earlier, each region has a different value. So that if there are more observation locations, it will be easier to make a prediction system because it is rich in a lot of data.

4. CONCLUSION

The Internet of Things (IoT) has revolutionized monitoring systems across various sectors, providing real-time data that enhances decision-making processes for faster responses. In industries such as agriculture and renewable energy, IoT applications enable the optimization of environmental conditions to ensure they are always at their most suitable levels. This real-time monitoring capability is vital for improving efficiency and productivity. In agriculture, IoT plays a significant role by improving crop productivity through effective temperature and humidity management. Similarly, in industrial settings, IoT systems are critical in preventing equipment damage by ensuring optimal environmental conditions are maintained.

Moreover, the DHT22 sensor is particularly effective in IoT applications where temperature and humidity monitoring is essential. Despite the DS18B20 sensor providing higher accuracy for temperature measurements, the DHT22 remains a popular choice due to its reasonable cost and adequate accuracy. It is well-suited for diverse environments such as greenhouses, server rooms, and storage spaces, making it a reliable and economical option for a wide range of IoT applications.

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