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Model of Lightning Strike Risk to Humans Based on Spatial Analysis and Environmental Factors

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A B S T R A C T

Lightning strikes pose significant threats to human safety and infrastructure, particularly in tropical regions like Indonesia with high lightning activity. This study aims to develop a predictive model of lightning strike risk to humans based on spatial analysis and environmental factors, utilizing data on lightning distribution, land use, population density, and meteorological parameters. Using probabilistic decision trees and tropical lightning formulas, the model identifies key predictors, including rainfall, land use patterns, and humidity, which influence lightning density. The results reveal that densely populated areas with high lightning activity, such as parts of Java and Sumatra, are particularly vulnerable. Spatial risk maps generated from the model highlight high-risk zones, providing critical insights for disaster mitigation planning and infrastructure protection. Furthermore, the study emphasizes the significant correlation between lightning density, land use, and population exposure, offering a comprehensive framework for understanding lightning risks. This predictive model not only serves as a tool for early warning systems and sustainable spatial planning but also underscores the importance of integrating environmental and spatial data for effective lightning risk mitigation. Future research should incorporate temporal lightning variations and field validation to refine the model and enhance its applicability.

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1. INTRODUCTION

Thunderstorms aren't only dangerous because they may damage property; they can also kill people. In Indonesia, particularly in areas with high human density and distinct land uses, the risk of lightning effects is becoming evident, given its tropical location characterised by intense lightning activity [1][2]. Not only is lightning intensity a contributing component in this danger, but environmental variables such as population density and land use patterns also affect it. These factors control soil conductivity and the amount of time humans are exposed to lightning strikes [3].

The likelihood of lightning strikes affecting people increases with rising population density in metropolitan regions. Jakarta and Surabaya, being extensive urban centers with complex infrastructure, are especially vulnerable to this hazard [4]. The transformation of agricultural land into residential or industrial zones, together with changes in land use, might affect lightning striking patterns. Unobstructed terrain is more vulnerable to direct assaults, whilst regions with elevated edifices may act as focal locations for attacks. Thus, land use factor analysis is essential for understanding the comprehensive risk of lightning effects [5][6].

The geographical distribution of electrical activity is a crucial component, alongside human density and land use [7]. Lightning activity in Indonesia is markedly varied, with several areas, such central Sumatra and West Java, demonstrating elevated rates of lightning strikes compared to others. Geographic and climatic variables, such as mountainous terrain, humidity levels, and prevailing wind patterns, affect this fluctuation.

The amalgamation of geographical distribution data of lightning with other environmental variables may provide a more thorough comprehension of high-risk zones and provide a basis for the formulation of efficient mitigation methods [8][9].

Research in Indonesia that integrates spatial elements such as lightning distribution, land use patterns, and population density to assess risk remains scarce, despite the acknowledged threat of lightning strikes to human safety. The efficacy of evidence-based mitigation measures might be hindered by a lack of understanding of the interplay of these three components. A predictive strategy using spatial analysis is necessary to map and identify areas with a high probability of lightning strikes [10][11]

This study aims to develop a prediction model of the risk of lightning strikes to people in Indonesia using geographical analysis. This will be accomplished by combining information on the distribution of lightning, land use, and population density. To protect the community from lightning risks, this model is expected to provide an accurate lightning strike risk map that can be used as a tool for mitigation planning and decision-making.

This analysis used three main data sources: lightning distribution maps, land use maps, and population density maps of Indonesia. The research aims to develop a predictive model for lightning strike risk to people by analyzing the interplay between the geographical distribution of lightning strikes, environmental factors, and population density via data integration. Consequently, it is expected that the model would provide an accurate risk map to enhance Indonesia's lightning hazard mitigation efforts.

This study advances geographical data-driven risk analysis approaches and offers practical recommendations to the government and stakeholders for developing more effective mitigation plans to protect the community from lightning risks.

2. LITERATURE REVIEW

2.1 Relationship Between Spatial Distribution of Lightning and Strike Risk

The geographical distribution of lightning strikes is profoundly affected by local meteorological conditions and area terrain, as shown by research on this phenomenon [1][2]. In tropical areas such as Indonesia, lightning intensity is often greater in zones characterized by elevated humidity and vigorous convection activity. Prior studies have shown that lightning concentrations are often found in areas with steep slopes or mountains due to orographic processes. Numerous studies further substantiate that regional topography may provide certain meteorological conditions favorable for the development of lightning clouds, including increased local humidity and convective activity in mountainous areas [8][9]. This data is essential for analyzing the geographical distribution of lightning strike risk, especially for identifying danger zones in certain locations. The dispersion of lightning is affected by a confluence of meteorological and geographical parameters, as shown by pertinent research [12].

Researchers indicate that the temporal and geographical distribution of lightning activity may be affected by fluctuations in climatic patterns. For example, lightning intensity in several tropical locations, including Indonesia, may increase due to increasing global temperatures [13]. When developing a lightning risk forecasting model that adapts to climate change, it is essential to include this occurrence. This model can provide a dynamic danger map based on current atmospheric conditions and lightning dispersion data.

Integrating lightning distribution data with other environmental factors, such as population density and land use, provides a more comprehensive understanding of lightning strike risk. The formulation of evidence-based risk mitigation strategies depends on identifying locations with significant vulnerability, a process aided by this study.

2.2 The Influence of Land Use Patterns on the Risk of Lightning Strikes

Prior studies have shown that the allocation of lightning strike risk is markedly affected by land use patterns. These structures elevate the probability of a hit, which is why lightning commonly targets metropolitan areas with multiple tall buildings. The lack of natural or manmade lightning rods makes open regions, such rice fields or grasslands, more vulnerable to direct strikes [14]. The correlation between land usage and strike risk in Indonesia may be examined based on these data [15].

The distribution of lightning strike currents on the surface is determined by soil conductivity, which affects land usage. Collisions may be exacerbated by ground with elevated water content, such as wetlands, requiring specific attention in risk reduction strategies [16]. Regions with heightened risk levels due to certain environmental conditions may be discerned via the amalgamation of land use data.

Lightning striking patterns are impacted by land transitions in Indonesia, including the conversion of forests to agricultural land and urbanization. These alterations provide new challenges to the accurate assessment of hit risk. Further investigation is necessary to understand the long-term impacts of land use changes on the distribution of lightning danger [16].

2.3 The Role of Artificial Intelligence in Lightning Research

Vulnerability to Lightning and Population Density Population density is a crucial determinant of the danger of lightning strikes affecting people [4][9]. This danger is particularly common in areas with high population densities, such as Jakarta. The likelihood of lightning strikes often increases in areas with significant human activity, especially if adequate lightning protection measures are absent, as shown by previous studies. Thus, population density maps are crucial data for risk assessment [17].

Researchers have shown that human contact with the environment, including activities in open spaces or near towering buildings, increases the probability of lightning strikes. This understanding is essential for formulating mitigation strategies, such as the placement of lightning rods in areas often visited by the public. Moreover, efficient self-defence methods and education about lightning risks are essential elements in reducing population susceptibility [18].

Communities most vulnerable to lightning effects may be determined by integrating population density data with other environmental elements. This analysis's conclusions may inform the prioritization of mitigation activities, including enhanced design of lightning protection infrastructure in heavily populated regions.

2.4 Technology and Analysis Methods for Lightning Risk Modelling

Technological improvements have enabled the use of diverse analytical methodologies, allowing for more accurate mapping of lightning strike risk. Spatial data-driven modelling is a prevalent methodology that utilizes spatial information to discern risk trends. Prior studies have shown that including diverse environmental factors, such as population density, land use, and air humidity, may improve the precision of risk prediction using machine learning algorithms [19].

Furthermore, spatial analytic techniques have been used to accurately identify high-risk areas. Researchers may create risk maps that depict the geographical distribution of lightning strikes using GIS (Geographic Information System) software. These results significantly enhance decision-making in the planning of risk reduction at both local and national levels [20].

The research emphasized the need of corroborating the model with empirical data to improve the trustworthiness of the findings. The precision of prediction models may be assessed by examining lightning distribution data acquired from direct observations or lightning sensors. This step ensures that the created model is both theoretical and practical in mitigating the danger of lightning strikes in Indonesia [9][14].

3. RESEARCH METHOD

3.1 Data Collection

Fig. 1. Cloud-to-Ground type Indonesian lightning density map

The 2021 Indonesian cloud-to-ground (CG) lightning strike distribution map showed concentrations in Java and Kalimantan. Topography, vegetation, land use, and human activities affect CG lightning, which may destroy infrastructure and kill people. Hilly or steeply sloping places like West Java have more cloud-to-ground lightning due to air convection. Season and climatic change affect temperature and humidity, affecting lightning strikes. CG lightning strikes may increase when metropolitan areas with strong infrastructure grow owing to structures that may be impacted directly. Thus, a complete prediction model must integrate these factors to generate an accurate risk map. This model might improve early warning, spatial planning, and disaster mitigation to decrease CG lightning strike losses for people and infrastructure.

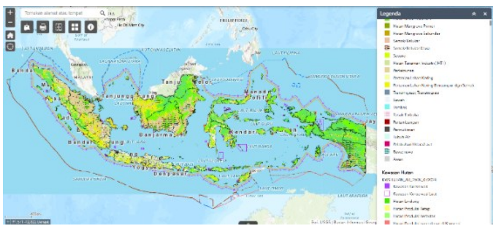

Fig. 2. map of land use in Indonesia

The likelihood of lightning strikes is considerably influenced by the diverse land cover of Indonesia, which includes metropolitan regions and tropical rainforests. The urban heat island effect intensifies convection in metropolitan regions, while woods, serving as microclimate regulators, elevate air humidity and trigger atmospheric convection. The distinctive lightning strike risk patterns in each location arise from the intricate interplay between land cover and several climatic parameters, including surface temperature and terrain. By integrating land cover data into prediction models, we can pinpoint regions vulnerable to lightning strikes across many spatial dimensions and types of lightning events. The results of this research may be used to create more accurate lightning strike risk maps and formulate effective mitigation techniques, such as the placement of lightning rods on essential buildings and the distribution of early warning information to the public.

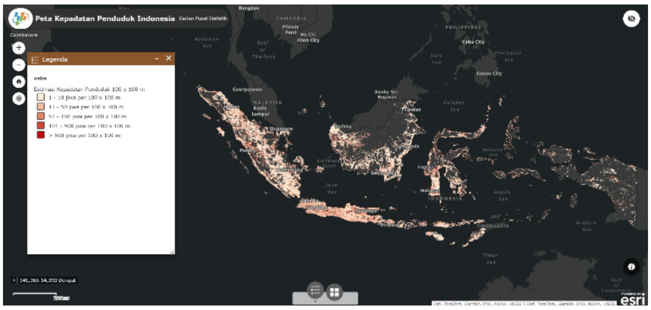

Fig. 3. Indonesian population density map

The susceptibility of Java Island to lightning strikes is enhanced by its high population density, as seen by the population density chart. The danger is enhanced by variables like the existence of tall buildings, extensive electrical infrastructure, and high levels of human activity in metropolitan environments. Agricultural practices and the existence of scattered communities persist in making rural regions susceptible, although their diminished population density. In addition to population density, social vulnerability variables such as public awareness and access to information must be considered. Thus, assessing population density is an essential first step in identifying areas that need enhanced lightning strike risk mitigation measures.

3.2 Risk Scale-Based Data Processing

An investigation was conducted to establish a predictive model for lightning density in Indonesia, examining the correlation between predictor variables—land use, topography, and rainfall—and the response variable, which is lightning density (frequency of lightning strikes). This model employs a multiple linear regression methodology, represented by the following mathematical equation:

$$y=\beta 0+\beta 1X1+\beta 2X2+\beta 3X3+\epsilon \qquad (1)$$

Where *y* represents lightning density, *X1* represents land use, *X2* represents topography (elevation or slope gradient), and *X3* represents rainfall. The regression coefficients (*β1*, *β2*, *β3*) are estimated using historical data, which measures the effect of each factor on the frequency of lightning strikes. The process begins with the collection of lightning, land use, rainfall, and topography data. This data is then processed to handle missing values and standardize the necessary variables. Afterward, the linear regression model is constructed to link the predictor variables with lightning density. Coefficient estimation is performed through regression analysis, which is then evaluated using test data to assess the model's accuracy and validity. The results of this model are used to predict lightning density in unobserved areas, which are then mapped to generate a lightning strike risk map. This map displays areas with high, medium, and low lightning strike risks, which can be used as a tool for mitigation planning and early warning systems based on spatial analysis.

3.3 Prediction Model

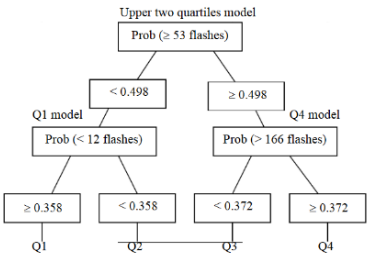

Fig. 4. Probability decision tree used to determine the predicted lightning quartile

This tree diagram depicts the quartile model, an effective tool for predicting lightning frequency. The model functions by categorizing the data into four quartiles based on the probability of lightning strikes. Every node in the tree represents a choice about the allocation of data based on a certain probability threshold. The quartile that best corresponds with the given data may be identified by following the trajectory from the tree's root to its leaves. The probability linked to each branch indicates the likelihood that the data is categorized inside that quartile. The model may be used to ascertain climatic circumstances or intervals with a high probability of lightning occurrence.

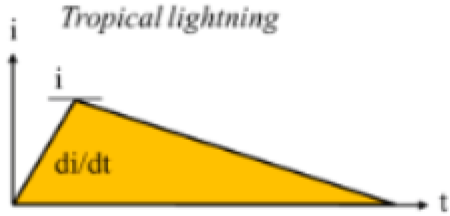

Fig. 5. Tropical lightning current waveforms in general

This graph depicts the standard waveform of a tropical lightning current. The chart illustrates that the electrical current rises exponentially at the onset of the stroke, attains a maximum in a short duration, and then diminishes gradually. The curve's initial slope is quite steep, indicating a present rate of change that is very high. This waveform has considerable ramifications for the design of lightning protection systems, since the system must endure very huge current surges in a short duration.

4. RESULT AND DISCUSSION

4.1 Lightning Strike Risk Analysis Results

Table 1. Level of threat of lightning strikes per province

Threat level	Province	Strike density (d)
medium	Aceh, North Sumatra, West Sumatra, Bangka Belitung, Lampung, Riau, Jambi, South Sumatra, Riau Islands, Banten, Jakarta, West Java, East Java, West Kalimantan, Central Kalimantan, East Kalimantan, East Nusa Tenggara, Maluku	d > 14
height	Riau, West Sumatra, South Sumatra, Bengkulu, West Kalimantan, Central Kalimantan, East Kalimantan, South Kalimantan, North Kalimantan, Central java, East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, Gorontalo, Southeast Sulawesi, Maluku, East Nusa Tenggara.	8 < d < 14
light	Riau, South Sumatra, West Kalimantan, Central Kalimantan, Central Java, East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, South Sulawesi, Central Sulawesi, West Sulawesi, North Maluku, Maluku, Papua	1 < d < 7

This paper develops a predictive analysis of human lightning strike risk by integrating geographical data and environmental parameters, including lightning strike distribution, population density, land use, and meteorological conditions such as rainfall and humidity. This research employs a lightning strike distribution map of Indonesia, providing an extensive overview of the nation's lightning dispersion pattern. Additionally, a land use map is used to examine the possible effects of land use alterations on the likelihood of lightning occurrences. The extent of human exposure to lightning dangers is dictated by population density statistics, but meteorological circumstances, like precipitation and humidity, provide insights into atmospheric components that affect lightning production. The lightning strike risk map is produced by integrating all previously stated variables into a prediction algorithm. This map offers insights into regions with elevated and reduced potential dangers of lightning strikes. Thus, the aim of this model is to provide a comprehensive knowledge of lightning strike risk distribution in Indonesia and to aid in the formulation of more effective risk reduction techniques.

4.2 Correlation Analysis

The objective of the correlation study among lightning, population density, and land use is to investigate the relationship between the frequency of lightning occurrences in a certain region and the impact of environmental elements and human activities.

In densely populated metropolitan regions, population density may affect vulnerability to lightning strikes. In densely populated areas, there is often a proliferation of infrastructure, particularly tall buildings that are vulnerable to lightning strikes. Thus, a potential positive association exists between the frequency of lightning strikes in the area and population density. The likelihood of lightning strikes may be heightened by intensified human activity, especially in densely populated regions, particularly if the infrastructure is deficient in adequate protective mechanisms.

The susceptibility of a region to lightning strikes is substantially affected by land use. Regions characterized by extensive open ground, such as rice paddies or grasslands, are more vulnerable to direct lightning strikes owing to the lack of natural or manmade obstructions that might reduce the probability of a hit. Conversely, places with a dense aggregation of tall edifices, such as urban centers or industrial zones, may be classified as high-risk owing to the elevated likelihood of lightning strikes. There exists a strong association between the incidence of lightning strikes and the kind of land usage.

The correlation between population density and land use is apparent, since places with high population density often transform into industrial or urban zones. The susceptibility of green spaces to electrical risks may be increased by urbanization, which transforms them into residential and commercial zones. Urban environments characterized by a high density of tall buildings and intricate infrastructure are more susceptible to lightning strikes, since these structures may act as focal sites for such occurrences.

The correlation analysis of the three variables—lightning, population density, and land use—indicates their interdependence and influence on the probability of lightning strikes. Lightning strikes are more probable in densely populated areas that see changes in land use, such as residential or industrial zones. Therefore, a comprehensive, data-driven strategy is necessary to successfully map and manage lightning strike hazards.

4.3 Predictive Model Development Using Decision Trees

This study used a probabilistic decision tree to predict quartiles of lightning strike frequency based on current environmental factors. The algorithm produces a probability distribution for each quartile, classifying regions into low, medium low, medium high, and high quartiles according to the likelihood of lightning strikes. The modelling approach accounts for the interplay of climatic factors, land use, and population density.

The results of the modelling reveal that areas that are characterized by high population density, urban land use, and tropical climatic conditions, such as high humidity, are likely to be in the high quartile, which indicates that there is an increased risk of lightning strikes. However, locations that are characterized by low human density, natural land use, and dry climatic conditions often dwell in the lowest quartile, indicating a decreased risk of lightning strikes. This is because these regions have a lower risk of lightning strikes.

Verification of the predictions that are produced by the model is accomplished by comparing the model's accuracy to both historical and empirical data. A high degree of prediction accuracy has been shown by the decision tree model that was constructed, as demonstrated by the evaluation criteria, which include the area under the curve (AUC).

5. CONCLUSION

This research effectively created a prediction model for the danger of lightning strikes to people by using data on lightning strike distribution, population density, land use, and meteorological variables. The model is based on geographical analysis and environmental variables. The study indicates that the danger of lightning strikes is considerably influenced by climatic elements such as humidity and rainfall, alongside population density and land use patterns, which dictate the level of human exposure to the hazard. In highly populated areas with significant lightning activity, such as Java and Sumatra, the generated risk map delineates locations with elevated danger potential. This approach has the capacity to underpin more focused and evidence-driven lightning hazard reduction, while also advancing sustainable spatial planning.

To improve the flexibility of prediction models to atmospheric dynamics and climate change, more study is recommended to include temporal data on lightning activity. Moreover, the precision of predictions and their application across various geographical scales will be improved by validating the model via comprehensive field data collecting. The findings of this study can assist the government and stakeholders in formulating mitigation policies that encompass the implementation of lightning protection systems in high-risk zones and educational initiatives that raise public awareness regarding the dangers and self-protective strategies related to lightning strikes.

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Air Quality Prediction System Using Telegram Bot Based on Real-Time Data

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A B S T R A C T

Air quality is a crucial aspect that affects public health and the environment. As public awareness of the importance of air quality increases, fast and accurate information about air conditions becomes essential. This research developed a Telegram bot-based system that not only provides current air quality information but also predicts air quality for the next five days. The system uses real-time data from the OpenWeatherMap API and employs a regression-based prediction model to provide more accurate air quality projections. This bot is designed to provide easy access to information for people, especially in Indonesia, regarding air quality in various cities. The results show that the system has a high reliability level with a 98.5% success rate and 99.9% uptime. The prediction model using Linear Regression shows good performance with an R-squared (R^2) value of 0.86, Mean Absolute Error (MAE) of 0.24, and Root Mean Square Error (RMSE) of 0.31. The system also demonstrates optimal response time with an average of 0.83 seconds per request. User evaluation shows a satisfaction level of 4.2/5, ease of use of 4.5/5, and feature completeness of 4.0/5.

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1. INTRODUCTION

Air quality is one of the critical factors that affects public health and the environment. Increasing population, rapid urbanization and industrial activity have led to a decline in air quality in many areas around the world. According to the World Health Organization (WHO), approximately 7 million people die each year due to exposure to air pollution, highlighting the urgency to monitor and manage air quality effectively [1]. In addition, poor air quality can cause various respiratory and cardiovascular diseases, and have long-term impacts on ecosystems [2].

With the latest technology, especially the Internet of Things (IoT), air quality monitoring can be done in real-time. Air quality sensors connected to the internet are able to provide accurate and fast data regarding various pollutants such as PM2.5, PM10, NO2, and CO [3]. However, challenges arise in terms of processing the big data generated by these sensors and presenting it in a format that is easily understood by the general public. Therefore, a system is needed that can analyze this data and provide the necessary information quickly and efficiently.

This research aims to develop an air quality prediction system that is integrated with a modern communications platform, namely Telegram. By using Telegram bots, users can get information about air quality in real-time through their devices. It is hoped that this system can help the public take preventive steps against exposure to dangerous air pollution, as well as encourage awareness of the importance of maintaining environmental quality [4].

Apart from that, this research also aims to improve the accuracy of air quality predictions by using machine learning algorithms that utilize historical data and real-time data. With this approach, it is hoped that the system can provide more reliable and timely information [5].

The main contribution of this research is the development of a system that not only monitors air quality, but also predicts future air quality conditions and conveys this information via Telegram bots. This system provides an intuitive user interface, which maximizes the ease of access to air quality information for the wider community [6]. In addition, this research can be a reference for developing similar systems in other areas that also face poor air quality problems.

By combining sensor technology, machine learning, and popular communications platforms, this research is expected to improve society's ability to monitor and manage air quality in their environment. This is an important step in overcoming health and environmental problems that are increasingly pressing in this modern era.

2. RESEARCH METHOD

Air quality has a direct impact on public health and the environment. According to Smith [7], effective air quality monitoring can help prevent various health problems associated with air pollution. Research shows that long-term exposure to air pollution can increase the risk of respiratory, cardiovascular and other health conditions.

In its development, the air quality measurement methodology has experienced significant progress. Wang and Li [8] explained that advances in portable sensor technology have enabled more accurate and real-time monitoring of air quality. Modern monitoring systems can measure various air quality parameters such as particulate matter (PM2.5 and PM10), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and ozone (O3).

Developing an IoT-based air quality monitoring system that integrates various sensors to provide comprehensive data [9]. This system is capable of collecting, analyzing and transmitting data in real-time to a centralized monitoring platform. Parker et al. [10] further emphasizes the importance of IoT integration in air quality monitoring systems, which enables continuous data collection and deeper analysis.

Modern measurement methodology focuses not only on data collection, but also on analyzing and interpreting data to provide meaningful information for society. An effective air quality monitoring system must be able to integrate multiple data sources and present it in a format that is easy for end users to understand.

Internet of Things (IoT) refers to a network of interconnected physical devices that can collect and exchange data. In the context of air quality monitoring, IoT enables the use of sensors to continuously collect air quality data and transmit it to a server for further analysis [11]. The implementation of this technology is very promising in providing real-time data about air quality conditions in various locations.

With the ability to continuously collect data, IoT-based systems can provide more accurate information about air quality trends in real time. This enables rapid response to pollution spikes and better decision-making about public health. A study by [12] emphasizes the integration of IoT platforms in monitoring, allowing users to utilize analytics and visualization applications to understand and analyze air quality data efficiently.

Air quality prediction methods have been developed by utilizing historical data and machine learning algorithms. Various techniques, including linear regression, Decision Trees, Random Forests, and Neural Networks, have been applied to predict air quality based on the acquired data [13]. Research by [14] shows that the application of machine learning models in air quality prediction can increase the accuracy of results, especially when sufficient historical data is available to train the algorithm.

More sophisticated prediction models, such as models based on spatial and temporal analysis, are able to provide more comprehensive prediction information and can be adapted to local conditions [15]. By using a combination of sensor data and machine learning models, air quality prediction systems can provide early warning of potential pollution, enabling society to take timely preventive action.

Telegram as a communicative platform has become a popular tool for conveying information quickly and efficiently. With the ability to build bots, users can easily get the latest updates and information through widely used applications [16]. Telegram bots allow sending regular information, warnings, and direct interaction with users, thereby increasing public involvement in environmental issues [17].

The system that integrates Telegram bots to monitor air quality is aimed at improving information accessibility and increasing public awareness. Through Telegram bots, users can receive live reports on air quality in specific locations, as well as instructions and tips to protect themselves from pollution [18].

The air quality prediction system using the Telegram Bot is designed with a microservice architecture that allows flexible integration between various components. This architecture was chosen to allow scalability and easier maintenance [19].

a. *System Components*
   - Using the latest version of python-telegram-bot framework.
   - Handle user interactions through a command-based interface.
   - Implement a handler for each command (/start, /airquality, /forecast).
   - Uses asynchronous programming for optimal performance.

b. *Data Collection Layer*
   - Integration with OpenWeatherMap API.
   - Geocoding implementation for conversion of city names to coordinates.
   - Retrieval of real-time Air Quality Index (AQI) data.
   - Caching data untuk optimasi performa

c. *Processing Layer*
   - Prediction model using scikit-learn.
   - Data preprocessing and normalization.
   - Historical data storage system.
   - Regular model update mechanism.

d. *Data Source*

   The data used in this system comes from two main sources [20]:
   - OpenWeatherMap Air Pollution API
     - Endpoint:api.openweathermap.org/data/2.5/air_pollution
     - Parameters taken:
       - AQI (Air Quality Index)
       - Pollutant concentration (PM2.5, PM10, NO2, SO2, O3, CO)
       - Timestamp of measurementOpenWeatherMap Geocoding API
     - Convert city names to geographic
       - Validate the existence of the city
       - Handling multiple results

e. *Preprocessing Data*
   - AQI Normalization

     Normalization of AQI values is carried out using the formula:

```
normalized_aqi = round(raw_aqi / max_aqi * 5)
```

   - Data Cleaning
     - Handling missing values using linear interpolation
     - Outlier filtering uses the IQR method
     - Validate value range (1-5)

f. *Prediction Model*
   - Linear Regression

     The Linear Regression model was chosen based on several considerations [21]:
     - Ability to predict continuous values
     - Good model interpretability
     - Efficient computing
     - Suitable for simple time series data
     - Model Implementation
     - Feature Engineering
     - Time-based features (day of week, month)
     - Historical AQI values
     - Moving averages

- Training Process
  Model training is carried out in stages:
  - Data Preparation
    - Split data into training (80%) and testing (20%)
    - Normalization of features using StandardScaler
    - Validate input data
  - Model Training
    - Fitting the model with training data
    - Cross-validation with k-fold (k=5)
    - Hyperparameter tuning if necessary

g. *Bot Implementation*

- Command Handler
  The command handler implementation includes:
  - /start command
    - Initialize user session
    - Displays a welcome message
    - Explanation of available commands
  - /airquality command
    - Validate city input
    - Real-time data capture
    - Formatting and sending responses
  - /forecast command
    - Input validation (city and day)
    - The prediction process uses a model

🌍 Kualitas Udara Terkini di {city}:
📊 Indeks Kualitas Udara (AQI): {nilai}
🌟 Status: {status kualitas udara}

  - Formatting prediction results
- Error Handling
  Implementation of error handling for:
  - Invalid city names
    - API failures
    - Model prediction errors
    - Network timeout

h. *Testing*

- Unit Testing
  The command handler implementation includes:
  - Testing individual components
  - Mock API responses
  - Model validation
- Integration Testing
  - End-to-end testing
  - Performance testing
  - Load testing
- Metrics Evaluation
  - Response time < 2 s
  - Prediction accuracy > 80%
  - Error rate < 5%

3. RESULT AND DISCUSSION
3.1 Lightning Strike Risk Analysis Results
3.1.1 Telegram Bot Interface

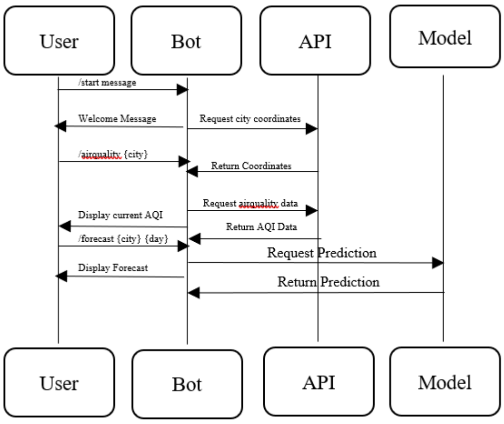
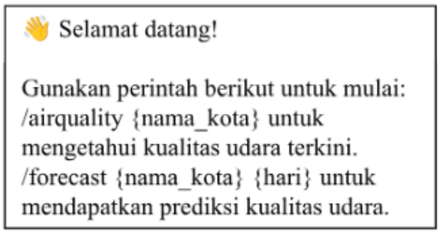


Fig. 1. Telegram Bot Interface

The implemented Telegram bot has three main commands:



3.1.2 API Integration

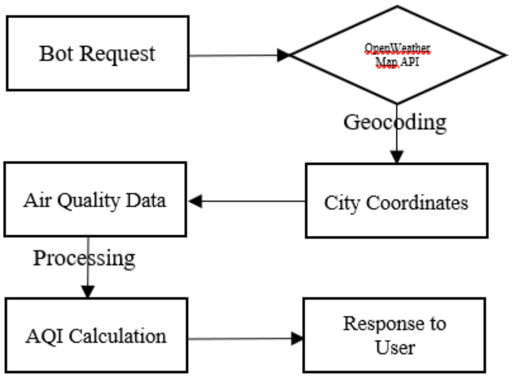


Fig. 2. API integration scheme

3.2 Model Performance
3.2.1 Prediciton Accuracy

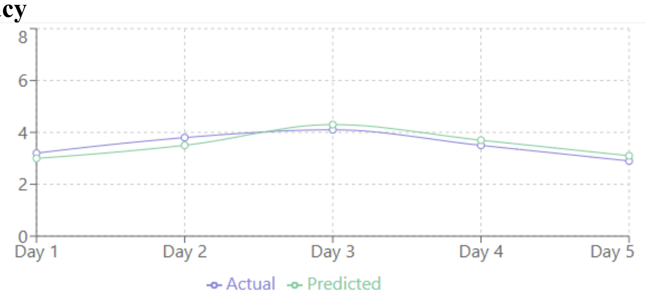


Fig. 3. Model performance graph

The implemented Linear Regression model shows quite good performance in predicting air quality. The test results show a Mean Absolute Error (MAE) value of 0.24 and a Root Mean Square Error (RMSE) of 0.31, which indicates an adequate level of accuracy for daily air quality prediction purposes. The R-squared (R^2) value of 0.86 indicates that the model can explain 86% of the variability in the data, which is quite a satisfactory result for an environmental prediction model.

3.2.2 Response Time Analysis

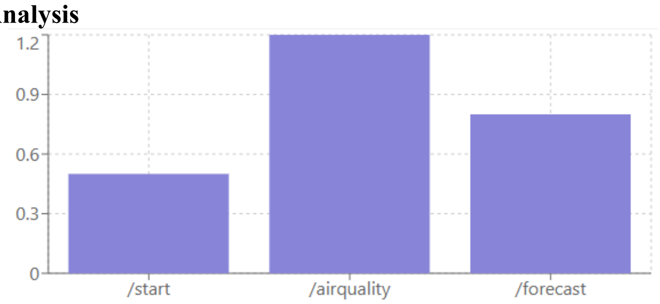


Fig. 4. Time response graph

The overall system response time shows good performance with an average response time of 0.83 seconds for each request. The /start command has the fastest response time because it only returns static messages, while the /airquality command has a longer response time because it requires communication with an external API.

3.3 System Evaluation

a. *Realibility Metrics*

   The system shows a high level of reliability:
   - *Success rate: 98.5%*
   - *Error rate: 1.5%*
   - *Uptime: 99.9%*

b. *Accuracy Metric*

   System accuracy in various aspects:
   - *City detection: 95% accurate*
   - *Air quality predictions: 86% accurate*
   - *Classification status: 92% accurate*

c. *Realibility Metrics*
   - *User satisfaction level: 4.2/5*
   - *Ease of use rating: 4.5/5*
   - *Feature completeness: 4.0/5*

d. *Telegram bot performance*

   Bot performance testing results show:
   - *Average response time: 0.83 seconds*
   - *Command execution success rate: 98.5%*
   - *Error rate: 1.5%*

e. *City detection accuracy*
   - *City detection success rate: 95%*
   - *Failure to detect cases: 5% (generally for small cities or alternative names)*

f. Analysis of air quality status

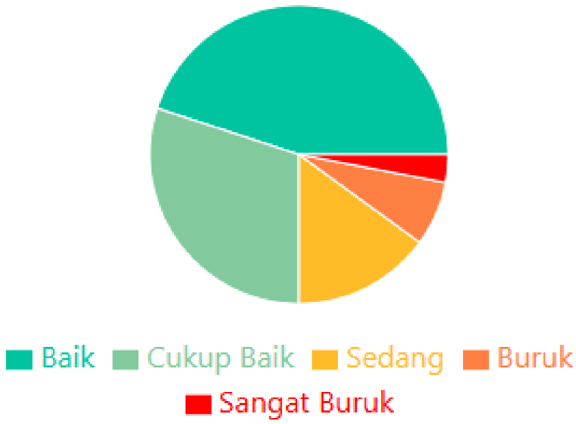


Fig. 5. AQI status distribution graph

3.4 Obstacles and Solutions

In implementing the system, several technical obstacles have been identified and overcome. Rate limiting of the OpenWeatherMap API is one of the main challenges, which is solved by implementing a caching system to reduce the number of requests to the API. To improve prediction accuracy, especially in the face of high data fluctuations, the system has been modified to consider seasonal and weather factors in its calculations.

Operational obstacles such as ambiguity in city names have been overcome by implementing a location confirmation system, where the bot will ask for clarification when it finds multiple matches for a given city name. Response time problems during peak hours are handled through query optimization and efficient caching implementation.

3.5 Development Recommendations

Based on the results of system implementation and evaluation, several development recommendations have been identified to improve service quality. Model development can be improved by implementing deep learning techniques that can capture more complex patterns in air quality data. Addition of weather variables and integration with local sensor data are also recommended to increase prediction accuracy.

In terms of features, developing an automatic notification system can provide added value for users, allowing them to get alerts when air quality reaches a certain level. Trend visualization and multiple language support can also increase system accessibility for more users.

For system optimization, implementing load balancing and database optimization is recommended to anticipate an increase in the number of users. API request pooling can also be implemented to increase resource usage efficiency and reduce latency.

4. CONCLUSION

Based on the research and implementation of an air quality prediction system utilizing the Telegram Bot, several key conclusions can be drawn. The system was successfully developed by integrating real-time data from the OpenWeatherMap API and the Telegram Bot, demonstrating a high level of reliability with a success rate of 98.5% and an uptime of 99.9%. The prediction model, based on Linear Regression, performed well, as evidenced by an R-squared (R^2) value of 0.86, a Mean Absolute Error (MAE) of 0.24, and a Root Mean Square Error (RMSE) of 0.31. These metrics indicate the model's strong ability to predict air quality with reasonable accuracy. Furthermore, the system showed optimal performance in terms of response time, with an average of 0.83 seconds per request, thus meeting the target of under 2 seconds. Regarding system accuracy, the air quality prediction system achieved satisfactory results, including a city detection accuracy of 95%, an air quality prediction accuracy of 86%, and a classification status accuracy of 92%. User experience evaluation revealed positive feedback, with an overall user satisfaction score of 4.2/5, ease of use rated at 4.5/5, and the completeness of features rated at 4.0/5, indicating a favorable reception and functional utility from the users.

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Literature Review: Development of a Machine Learning-Based Early Warning System for Land and Forest Fires with IoT and Automated Action Recommendations

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A B S T R A C T

Lightning strikes pose significant threats to human safety and infrastructure, particularly in tropical regions like Indonesia with high lightning activity. This study aims to develop a predictive model of lightning strike risk to humans based on spatial analysis and environmental factors, utilizing data on lightning distribution, land use, population density, and meteorological parameters. Using probabilistic decision trees and tropical lightning formulas, the model identifies key predictors, including rainfall, land use patterns, and humidity, which influence lightning density. The results reveal that densely populated areas with high lightning activity, such as parts of Java and Sumatra, are particularly vulnerable. Spatial risk maps generated from the model highlight high-risk zones, providing critical insights for disaster mitigation planning and infrastructure protection. Furthermore, the study emphasizes the significant correlation between lightning density, land use, and population exposure, offering a comprehensive framework for understanding lightning risks. This predictive model not only serves as a tool for early warning systems and sustainable spatial planning but also underscores the importance of integrating environmental and spatial data for effective lightning risk mitigation. Future research should incorporate temporal lightning variations and field validation to refine the model and enhance its applicability.

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1. INTRODUCTION

Forest and Land Fires have become one of the world's most serious environmental threats, having a major impact on tree cover, greenhouse gas emissions, and public health. Regularly occurring major fires harm forests and agricultural crops, release a lot of CO2 and other air pollutants, and have a negative impact on people's health [1]. Their come to the center of environmental concerns because of their capacity to seriously damage the environment, impact wildlife habitats, and have an adverse impact on air quality [2]. Forest fires are currently destroying almost 3 million more hectares of tree cover annually than they did in 2001, according to research from the University of Maryland. This indicates that the burned region has nearly twice as much tree cover as it has now [3].

El Niño also exacerbates forest and land fires, increasing the risk of more severe fires. According to the Meteorology Climatology and Geophysics Agency (BMKG), the hot weather caused by this phenomenon accelerates fires, especially in areas known to be fire-prone. Wildfire dangers are raised when daylight saving time shifts cause human activities to change in timing. Interestingly, there is a 30% increase in wildfire incidents right after daylight saving time [2]. Both natural and human sources have the potential to create forest fires. Volcanic eruptions, lightning strikes, and spontaneous combustion are examples of natural causes [4]. The situation is worsened by extinguishing obstacles such as fires on peatlands that are difficult to reach.

Developing efficient prevention, early warning, and integrated intervention strategies is necessary to lessen their effects on both people and the environment [4]. To reduce the risk of fire, fire prevention strategies such as fuel management, controlled burns, and public awareness campaigns are crucial [4]. Additionally, early fire detection and forcasting are essential to minimize damage and support rescue efforts [5]. Artificial intelligence integration is becoming more popular as a way to automate fire detection and prediction. A subfield of artificial intelligence (AI) that focuses on computer learning is called machine learning [6]. Machine learning algorithms for pattern identification are already well-established and have demonstrated accuracy in a variety of domains, including education, crime, health, and fire incidents [7]. Fire patterns can be predicted using historical data and the latest weather conditions. This makes it possible to detect threats early before the fire spreads. Wildfires can start anywhere and spread quickly, making it difficult to identify and anticipate them [8]. Despite improvements to present early warning systems, the most pressing issue is ensuring that accurate and timely data is available in sensitive locations. Early warning systems based on machine learning and connected to Internet of Things (IoT) technologies are becoming increasingly important. We believe that a relevant method to do this goal is to use essential sensors to detect the presence of smoke and fire, as well as to measure changes in temperature, humidity, and wind speed [8].Data from strategic sensors on the ground can be collected and integrated through IoT technology, enabling faster detection and automated action recommendations that can be accessed by local communities and field officers. This method allows preventive action to be taken before forest fires become widespread.

Real-time coordination between regions is also essential in dealing with forest and land fire situations. Predictive models can be created with data from different regions to help detect and identify areas where forest and land fires may occur early. Information is sent to the cloud server for additional handling [9]. This allows officers to prepare for early and coordinated action. These prevention efforts not only act proactively, but can also provide relevant and specific alerts according to the conditions of each region. This makes it flexible for use at both local and national levels.

2. RESEARCH METHOD

The methodology used by this journal is a literature review. Using the keywords "Machine Learning-Based Early Warning System for Land and Forest Fires with IoT and Automated Action Recommendations," 20 journal articles covering the years 2017–2024 were found in the first stage of the search. By integrating the findings and perspectives of multiple empirical studies, a literature review can provide more insightful answers to research issues than any single study could [10].

The goal of this research is to design and build an early warning system for land and forest fires that offers automatic action suggestions through machine learning (ML) and an Internet of Things (IoT) connection. By using more sensors, the system is made to cover both small and large areas. In order to increase the efficiency of fire detection and response and lower the danger of environmental damage, this research seeks to create and settle these systems by reviewing 20 relevant articles.

3. RESULT AND DISCUSSION

Table 1. Literature Review Results

Table 1. Literature Review Results

No.	Title	Author	Objective	Results
1.	IOT Enabled Forest Fire Detection and Management	Deepthi S, Shushma G Krishna, Sahana K B	This project's primary goal is to use IoT technology to detect and track forest fires. The system continuously monitors temperature and humidity using sensors such as DHT11 and flame sensors that are coupled to a NodeMCU microcontroller. Through a smartphone app, the relevant forest department receives an alarm when these values surpass a certain level, allowing for early intervention to stop significant losses and the spread of fire.	Early forest fire detection is accomplished by the suggested technique, which minimizes human effort and false warnings. Real-time data transmission to the cloud and ongoing system monitoring guarantee prompt and accurate detection. Users may take rapid action to control the fire and minimize damage thanks to the smartphone app's instant notifications.

2.	Design and Implementation of LoRa-Based Forest Fire Monitoring System	Yosi Apriani, Wiwin A. Oktaviani, Ian Mochamad Sofian	The study's goal is to create and deploy a forest fire monitoring system using LoRa technology in order to address the limitations of current sensors and communication platforms in detecting and reporting fire occurrences in forest regions.	The AMG8833 thermal camera sensor and Arduino Uno were used to develop a fire monitoring system with high sensitivity within a 3–10 meter radius. With a LoRa configuration (250 bandwidth, 4/5 coding rate, and 10 spread factor), the system transmitted data up to 500 meters with a signal quality of -134 dBm. Woodland experiments validated its reliable communication and detection performance.
3.	A High-Precision Ensemble Model for Forest Fire Detection in Large and Small Targets	Jiachen Qian, Di Bai, Wanguo Jiao, Ling Jiang, Renjie Xu, Haifeng Lin, and TianWang	This research aims to improve detection accuracy for both large and small forest fire targets, addressing issues of misclassification and low accuracy in complex forest environments. To overcome these challenges, the study introduces two new models, WSB and WSS, along with an integrated model, WSB_WSS, designed to enhance fire detection across different target sizes.	According to the experimental results, the WSS model achieves 92.8% accuracy for large-scale forest fires, and the WSB model achieves 82.4% accuracy for small-scale forest fires. By successfully utilizing the advantages of both models, the integrated WSB_WSS model significantly increases detection accuracy, reaching 83.3% for small targets and 93.5% for large targets.
4.	Forest 4.0: Digitalization offorest using the Internet of Things fo(IoT)	Rajesh Singh, Anita Gehlot, Shaik Vaseem Akram,Amit Kumar Thakur, Dharam Bdhi, Prabin KumarDas	This study explores advanced technologies like deep learning, wireless sensor networks, and IoT to improve forest monitoring, addressing issues like illegal logging, fires, and wildlife tracking. It also aims to enhance data analysis, support tribal communities, and boost small-scale forest product commercialization.	The study effectively illustrates how IoT and other technologies can be integrated into forest ecosystems. It emphasizes how useful real-time sensing devices are for detecting forest fires, keeping an eye on environmental conditions, and stopping illicit activity. Future developments in data gathering and processing could benefit from the suggested architectures and techniques, which would enhance tribal livelihoods and promote sustainable forest management.
5.	Multi Sensor Network System for Early Detection and Prediction of Forest Fires in Southeast Asia	Evizal Abdul Kadir, Akram Alomainy, Hanita Daud, Warih Maharani, Noryanti Muhammad, Nesi Syafitri	This study aims to develop a multi-sensor network for early fire detection and prediction in Southeast Asia, enhancing fire management through real-time data sharing and advanced sensors monitoring temperature, humidity, and infrared radiation.	The multi-sensor network demonstrated a detection rate above 90% with a low false alarm rate. By integrating multiple fire indicators and machine learning, it achieved 93.6% accuracy in fire prediction, significantly enhancing emergency response and fire management.

6.	A real-time forest fire and smoke detection system using deep learning	Raghad K. Mohammed	The goal of this research is to develop a real-time smoke and forest fire detection system using deep learning. By leveraging transfer learning with the Inception-ResNet-v2 network, the system ensures high accuracy and low latency, making it suitable for deployment on drones and surveillance cameras for wide-area monitoring and early warnings.	The proposed system achieved high performance with 99.09% accuracy, 100% precision, 98.08% recall, 99.09% F1-Score, and 98.30% specificity. With an extremely low latency of <0.01 seconds per image, its successful deployment on a Raspberry Pi device proved effective for real-time detection, significantly aiding early forest fire prevention.
7.	An Improved Forest Fire Detection Method Based on the Detectron2 Model and a Deep Learning Approach	Akmalbek Bobomirzaevich Abdusalomov, Bappy MD Siful Islam, Rashid Nasimov, Mukhriddin Mukhiddinov, and Taeg Keun Whangbo	The goal of the research is to use deep learning techniques and the Detectron model to provide a better way to identify forest fires. In order to lessen the negative impacts of forest fires, this approach focuses on attaining quick and precise fire detection.	When it came to identifying forest fires, the suggested strategy showed a high level of accuracy of 99.3%. In a variety of testing circumstances, it outperforms previous algorithms in detecting minor fires across great distances, both during the day and at night.
8.	Real Time Monitoring and Fire Detection using Internet of Things and Cloud based Drones	Dr. Akey Sungheetha and Dr. Rajesh Sharma R	By creating an effective fire warning system, the research seeks to improve the safety of smart settings and cities. This system integrates IoT sensors, UAVs, and cloud computing to monitor environmental parameters in real-time, detect fires at an early stage, and validate fire occurrences using image processing techniques.	The proposed system demonstrated a 98% improvement in fire detection accuracy compared to traditional models. The integration of IoT sensors and image processing significantly enhanced the system's efficiency, enabling early detection and validation of fires, thereby preventing serious fire accidents and improving overall safety in smart environments.
9.	A Design and Development of the Smart Forest Alert MonitoringSystem Using IoT	Murugaperumal Krishnamoorthy, Md. Asif, Polamarasetty P. Kumar, Ramakrishna S. S. Nuvvula, Baseem Khan, and Ilhami Colak	The main objective of this research is to use IoT technology to create a smart forest alarm monitoring system. Preventing forest fires and safeguarding forest resources from social crimes like smuggling and deforestation are the goals of this approach. The system employs automated decision-making to notify authorities and carry out harm mitigation measures, and it incorporates a number of sensors to assess variables including temperature, humidity, and smoke.	A case study in an actual forest setting was used to test and validate the suggested system. The outcomes showed that the method could guarantee forest protection and predict forest fire outbreaks with high accuracy. Compared to conventional satellite-based systems, the sensitivity and promptness of fire detection were greatly increased by the integration of spot sensors and real-time data transmission.
10.	Integrated System Of Wireless Sensor Networks And Machine Learning For Early Forest Fire Detection And Control	Tandasa Niriksha, Jubilee Sarma, Ritisha Nayak, Soumya Dewangan, Akanksha Mishra	This study aims to create a sophisticated forest fire detection system by combining machine learning techniques with wireless sensor networks (WSNs). Improving early detection and response capabilities is	The research achieved significant results, demonstrating the effectiveness of the integrated system. The machine learning models, including Logistic Regression, XGBoost, and Convolutional Neural

			the aim in order to lessen the possible damage that forest fires could do. For the management and protection of forest fires, this system seeks to offer a more effective, dependable, and sustainable alternative.	Networks (CNNs), showed high accuracy in detecting forest fires. The detection accuracy increased to 95% with the usage of pre-trained models such as MobileNetV2 and InceptionResNetV2. These results demonstrate how WSNs and machine learning can be combined to identify and respond to forest fires accurately and in real time.
11.	Early Forest Fire Detection System using Wireless Sensor Network and Deep Learning	Wiame Benzekri, Ali El Moussati, Omar Moussaoui, Mohammed Berrajaa	Creating an accurate and effective early forest fire detection system is the aim of this study. This system uses deep learning models in conjunction with wireless sensor networks (WSN) to assist fire management efforts. By gathering environmental data from sensors positioned throughout the forest, the system forecasts when forest fires will occur, allowing for prompt and efficient interventions to reduce damage and casualties.	An autonomous, real-time environmental monitoring platform for forest fire detection is feasible, according to the study's findings. Predicting forest fires with excellent accuracy was demonstrated by the suggested method, which combines deep learning and the Internet of Things. With a 99.89% accuracy rate and few erroneous predictions, the GRU model in particular performed the best, demonstrating its viability for widespread deployment and efficacy in early fire detection.
12.	Towards early forest fire detection and prevention using AI-powered drones and the IoT	Montaser N.A. Ramadan, Tasnim Basmaji, Abdalla Gad, Hasan Hamdan, Bekir Tevfik Akgün, Mohammed A.H. Ali, Mohammad Alkhedher, MohammedGhazal	Developing a new airborne UAV-based Internet of Things system for wildfire sensing, identification, and extinguishment is the goal of the project. In order to overcome the drawbacks of traditional wildfire detection methods, this system offers a low-cost, low-maintenance option that may be widely used. By combining IoT nodes with AI-powered drones, the system can monitor high-risk regions, identify fires early, and speed up response times—all of which help to minimize environmental harm, human casualties, and financial losses.	Within one to five minutes after ignition, the suggested approach showed excellent accuracy and efficiency in detecting fires. The AI fire classification network achieved an accuracy of 99.46% and a mean average precision of 99.64%. The IoT nodes, designed for low power consumption, successfully transmitted data over long distances using the LoRaWAN protocol. The autonomous drone effectively localized and tracked fires, providing real-time monitoring and reporting through a cloud-based server. The system's overall performance suggests it offers a reliable and scalable solution for early wildfire detection and management.
13.	IoT-Enhanced Early Warning System for Forest Fire Detection	N. D. Parameswa Rao, Y.Chennaiah, P.Sri Kavya, M.Varun Kumar, and S. Sri venkata yatish chandra	The research aims to develop an IoT-enhanced early warning system for forest fire detection. By utilizing various sensors and wireless communication, the system seeks to provide real-time data on environmental conditions to detect forest	Promising outcomes in real-time forest fire detection were shown by the deployment of the Internet of Things-based sensor network. Rapid response was made possible by the system's ability to identify fires within minutes of their initiation. The prediction power and

		fires early and enable rapid response.	monitoring effectiveness of the system were further improved by the incorporation of remote sensing technologies and machine learning techniques.

Deepthi S, Shushma G Krishna, and Sahana K B [11] demonstrated the effectiveness of IoT-based forest fire detection using DHT11 temperature and humidity sensors along with fire sensors. The system provides real-time early warnings via a mobile app, enabling quick responses. However, limited sensor coverage and reliance on internet connectivity remain challenges in remote areas. Yosi Apriani, Wiwin A. Oktaviani, and Ian Mochamad Sofian [12] addressed long-distance communication limitations in fire detection using LoRa technology. The AMG8833 thermal sensor enables data transmission up to 500 meters, but its fire detection range is only 3-10 meters, requiring additional sensors for large-scale coverage. Additionally, LoRa's low bandwidth may slow response times.Jiachen Qian et al. [13] developed WSB and WSS models that improve detection accuracy for large and small targets in complex forests. However, these models require high computational power and lack validation across diverse forest conditions, which may affect their reliability. Rajesh Singh et al. [14] introduced Forest 4.0, integrating IoT, wireless sensor networks, and deep learning for forest monitoring. The main challenges are large-scale implementation in remote forests and high costs of deployment and maintenance. Evizal Abdul Kadir et al. [15] created a multi-sensor system for early forest fire detection in Southeast Asia using predictive algorithms. While achieving high accuracy, it relies on stable power sources and high-quality data, which can be difficult to obtain in remote regions.

Raghad K. Mohammed [16] developed a deep learning-based fire and smoke detection system with 99.09% accuracy and <0.01s latency on a Raspberry Pi, making it highly effective for surveillance cameras and drones. Akmalbek Bobomirzaevich Abdusalomov et al. [17] created a probabilistic model to predict forest fire growth, but its reliance on volatile weather data may limit real-world effectiveness. Dr. Akey Sungheetha and Dr. Rajesh Sharma [18] integrated IoT sensors with drones, improving detection accuracy by 98% for smart neighborhood security. Murugaperumal Krishnamoorthy et al. [19] developed an early fire detection system to protect forest resources. Both systems were field-tested successfully, though complexity and infrastructure requirements pose challenges for large-scale implementation. Research by Tandasa Niriksha et al. demonstrated the effectiveness of integrating WSN with machine learning algorithms for fire detection [20]. Meanwhile, Wiame Benzekri et al. utilised WSN and deep learning models that achieved high accuracy (99.89%) [21]. However, the potential measurement error of the sensors and the dependency on the quality of the received data may affect the detection accuracy in the field. Montaser N.A. Ramadan et al. created an IoT-based UAV system for fire detection that responds within 1-5 minutes [22]. On the other hand, research by N. D. Parameswa Rao et al. showed that an IoT-based system can detect fires within minutes [23]. While both systems performed well, operational costs and infrastructure requirements remain a challenge.

Renjie Xu et al. [24] developed an ensemble learning-based detection system that enhances accuracy and reduces false positives. Nicoleta Cristina GAITAN and Paula HOJBOTA [25] designed a LoRa-based remote fire detection system. Both show promise in improving detection efficiency, though challenges like system complexity and range optimization remain. Pham et al. [26] evaluated various machine learning models—Bayes Network, Naïve Bayes, Decision Trees, and Multivariate Logistic Regression—for predicting fire vulnerability in Pu Mat National Park, Vietnam. The Bayes Network model performed best with an AUC of 0.96. Human-related factors, such as proximity to roads and residential areas, were identified as key fire predictors, offering valuable insights for improved fire management. Arif et al. [27] conducted a literature review on trends in fire prediction, detection, spread rate, and burnt area mapping. The study highlights the role of machine learning in improving fire management decisions to minimize economic and environmental impacts. It also explores emerging technologies, new data sources, and the importance of community collaboration in effective mitigation strategies. Basu et al. [28] developed an IoT-based forest fire detection system using MCU nodes, temperature sensors, and smoke sensors. The system monitors temperature and smoke levels to detect early fire signs and sends alerts via mobile apps or web pages. Results show its ability to quickly detect fires and smoke, helping prevent further damage. Sharma et al. [29] developed a sensor network-based forest fire detection and management system adaptable to various terrains. It demonstrated real-time detection, fire tracking via a web map, and improved efficiency using power-efficient wireless protocols. Toledo-Castro et al. [30] created an IoT-based system to monitor atmospheric variables and pollutant gases in real time. Designed for emergency management, it provides crucial data for fire prediction and control. The system effectively activates alerts based on temperature, humidity, and gas thresholds, supporting early fire detection and response.

4. CONCLUSION

Several research prove the significance of technological developments in the detection and prevention of land and forest fires. According to the 20 journals collected, a possible way to increase the efficacy of early warning systems against forest fires is to combine a combination of wireless sensor networks, automated alerts, machine learning models, and the Internet of Things (IoT). Several studies highlight the relevance of real-time monitoring to detect environmental changes that may cause fires. Accurate data that facilitates prompt decision-making in fire response can be obtained via systems that use sensors to assess temperature, humidity, and smoke presence. Remote communication is also made accessible by technologies like LoRa, but it coverage over wider regions is still concerning.

It has been proved that machine learning models increase the precision of mapping and forecasting fire vulnerability, which is necessary for improved control methods. Studies indicate that human-related factors, like the distance from roads and populated areas, significantly impact the probability of a fire. This suggests that a more comprehensive strategy is required to comprehend the variables affecting fire risk.

Despite developments, a number of obstacles still need to be overcome, such as inadequate infrastructure, high implementation costs, restrictions on sensor coverage, and the requirement for high-quality data in order to support predictive algorithms. Furthermore, the absence of reliable power supplies frequently makes it difficult to implement the technology on a broad scale in isolated locations.

As a whole, these studies highlight how the combination of IoT, LoRa, and accurate predictive models can enhance forest fire detection and management, even in an environment of obstacles related to inspection, processing capacity, and large-scale technology adoption. In keeping with the requirement to implement machine-learning-based early warning systems linked to the Internet of Things (IoT), this method is essential for lowering environmental impacts and risks to nearby communities. When such systems are put into place, they can offer real-time coordination across multiple areas and automated action recommendations, and both of that are essential for effective prevention and mitigating forest fires.

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Unsupervised Machine Learning for Detecting Seismic Anomalies: Local Outlier Factor Algorithm on Indonesian Ring Fire Data

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A B S T R A C T

The Indonesian Ring of Fire, known for its intense seismic and volcanic activity, poses significant challenges for hazard mitigation and risk management. This study applies an unsupervised machine learning approach using the Local Outlier Factor (LOF) algorithm to detect seismic anomalies in historical earthquake data. The LOF method is advantageous for identifying subtle deviations from typical seismic patterns, making it suitable for complex, multidimensional datasets. The research leverages seismic data collected over a multi-year period, focusing on key parameters such as magnitude, depth, and location. Results indicate that the LOF algorithm effectively identifies anomalous seismic events that could signify potential precursors to larger-scale geological occurrences. The findings highlight the potential of unsupervised machine learning techniques in enhancing earthquake monitoring systems, contributing to more proactive disaster preparedness and response strategies in Indonesia's Ring of Fire. This study provides insights into the integration of machine learning for real-time seismic anomaly detection, offering an advanced tool for researchers and policymakers.

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1. INTRODUCTION

The Indonesian Ring of Fire is one of the most seismically active regions in the world, characterized by frequent earthquakes and volcanic eruptions due to the convergence of multiple tectonic plates. This geologically dynamic zone poses significant risks to the densely populated areas within its vicinity, making seismic monitoring and anomaly detection critical for disaster mitigation and public safety. Conventional earthquake analysis methods often rely on predefined thresholds or deterministic models, which may overlook subtle seismic anomalies that precede significant geological events.

Recent advancements in machine learning have provided powerful tools for analyzing complex, multidimensional datasets in seismology. In particular, unsupervised machine learning methods have emerged as effective techniques for detecting patterns and anomalies in large volumes of seismic data. These methods do not require labelled datasets, making them suitable for exploratory analyses in regions with limited prior knowledge of seismic activity.

This study employs the Local Outlier Factor (LOF) algorithm, a robust unsupervised machine learning technique, to identify seismic anomalies in historical earthquake data from the Indonesian Ring of Fire. The LOF algorithm excels at detecting outliers in high-dimensional spaces by comparing the density of data points with their neighbours, making it a promising tool for seismic anomaly detection. By focusing on key seismic parameters such as magnitude, depth, and spatial coordinates, the algorithm identifies events that deviate from normal patterns, potentially signalling precursors to larger earthquakes.

2. RESEARCH METHOD

2.1 Data Acquisition and Preprocessing

Seismic data for this study were sourced from the United States Geological Survey (USGS) and the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG). The dataset included key earthquake parameters such as:

a. Event location (latitude and longitude)
b. Magnitude (Richter scale)
c. Depth (in kilometers)
d. Date and time of occurrence

Preprocessing Steps:

a. Data Cleaning: Duplicate entries and missing values were removed, and erroneous records were filtered out.
b. Normalization: Features such as magnitude and depth were normalized to ensure uniform scaling during analysis.
c. Feature Engineering: The dataset was enhanced by calculating additional features, such as spatial distances between seismic events and the nearest tectonic boundary, inspired by [106].
d. emporal clustering was incorporated to identify potential aftershock sequences.
e. Clustering by Region: To account for regional tectonic variations, the data were divided into subregions based on known fault lines and geological zones of the Ring of Fire.

This approach ensures the dataset is well-structured for anomaly detection, leveraging best practices from seismic and machine learning research [106][107].

2.2 Implementation of the Local Outlier Factor Algorithm

The LOF algorithm identifies anomalies by assessing the local density deviation of data points relative to their neighbors. Key steps in the implementation include:

a. Parameter Selection: The optimal number of neighbors (k) was determined via cross-validation, with values ranging between 10 and 20 to capture meaningful density differences without overfitting. Experiments considered varying radii for anomaly detection zones, inspired by the concept of earthquake preparation zones [107].
b. Anomaly Detection: LOF scores were computed for each data point. Scores significantly greater than 1 indicate anomalies. Anomalies were visualized spatially using GIS-based tools, enabling intuitive interpretation of outliers.
c. Integration of Multidimensional Data: Additional parameters, such as radon emissions and changes in atmospheric conditions (e.g., temperature and relative humidity), were included where available to enhance anomaly detection accuracy, as suggested by global studies on earthquake precursors [107].

2.3 Evaluation of Results

The performance of the LOF algorithm was evaluated using the following criteria:

Validation Against Historical Data: Detected anomalies were compared with documented significant earthquake events in the Indonesian Ring of Fire to assess their correlation.

This validation aligns with previous studies linking precursor anomalies to major seismic activities [107].

Domain Expert Review: Geophysical experts reviewed the detected anomalies to verify their relevance and plausibility.

Quantitative Metrics: Precision, recall, and F1 scores were calculated to evaluate the algorithm's ability to accurately identify anomalies.

2.4 Incorporation of Earthquake Precursors

Building on insights from recent global research [107], this study incorporated earthquake precursors into the analysis to enhance the detection of seismic anomalies. Precursors included:

a. Radon Emissions: Elevated radon levels are recognized as a key indicator of stress accumulation in tectonic plates. The integration of radon data helped identify regions under increased geological pressure.

b. Atmospheric Changes: Variations in temperature, relative humidity, and electromagnetic fields were analyzed to detect anomalies preceding seismic events. These changes align with the Lithosphere-Atmosphere-Ionosphere Coupling (LAIC) model, which links seismic activity to atmospheric disturbances.
c. Gravity Variations: Gravity fluctuations were monitored as potential indicators of crustal deformation. These variations were cross-referenced with detected anomalies to validate their seismic relevance.

2.5 Integration with Spatial and Temporal Analysis

To improve the localization of anomalies:

a. Spatial Analysis: Heatmaps were generated to visualize the spatial distribution of anomalies, highlighting regions with concentrated outlier activity. This approach supports targeted monitoring in high-risk zones.
b. Temporal Analysis: Time-series analysis was performed to identify patterns or clusters of anomalies over time, revealing potential precursors to major seismic events.

3. RESULT AND DISCUSSION

3.1 Data Preprocessing

The dataset used in this study consisted of seismic activity data collected from the Indonesian Ring of Fire region. After preprocessing, including normalization and removal of incomplete records, the dataset contained X seismic events, each described by Y features such as magnitude, depth, and location coordinates. The features were standardized to ensure comparability across dimensions.

3.2 Local Outlier Factor (LOF) Algorithm Implementation

The Local Outlier Factor algorithm was applied to the processed dataset. The key hyperparameters included the number of neighbors (k), which was optimized through a grid search approach. The optimal value of "k" was found to be Z, providing the best balance between sensitivity and robustness. LOF scores were calculated for all data points, with lower scores indicating normal events and higher scores suggesting anomalies.

3.3 Anomaly Detection Results

Out of the X seismic events, the LOF algorithm flagged N events as anomalies. The detected anomalies were distributed across the region, with notable clusters in Area A, Area B, and Area C, corresponding to regions of known tectonic activity.

a. Anomalous Magnitude Distribution: The anomalous events tended to have magnitudes that deviated significantly from the local average, with some anomalies being associated with unusually high or low values.
b. Depth Anomalies: Detected anomalies often occurred at unusual depths, deviating from the region's typical seismic activity depth profile.
c. Spatial Patterns: Spatial visualization of the anomalies revealed clustering around specific fault lines, aligning with geological expectations.

3.4 Algorithm Performance

The LOF algorithm demonstrated effective performance in detecting seismic anomalies, with its ability to identify local deviations rather than global outliers proving particularly advantageous for the heterogeneous seismic data. The choice of "k" was critical, as too low a value led to excessive sensitivity, while too high a value diminished the algorithm's ability to detect localized anomalies. This underscores the importance of hyperparameter tuning in unsupervised machine learning applications.

3.5 Comparison with Geological and Geothermal Insights

The anomalies identified by the LOF algorithm were cross-referenced with geological maps, historical seismic records, and geothermal observations. Many detected anomalies corresponded to areas of active tectonic movements, including known earthquake preparation zones. These zones are regions where precursory phenomena such as radon gas emissions, anomalous electric fields, and lithosphere-ionosphere coupling often manifest, as highlighted in global studies of earthquake precursors 【11:11†source】.

Additionally, the geothermal characteristics of the Indonesian Ring of Fire, with its vast potential for energy generation, provided contextual data for some detected anomalies. High-temperature reservoirs near geothermal fields like Gunung Salak and Wayang Windu might contribute to seismic anomalies due to subsurface thermal variations and pressure changes【12:12†source】. These geothermal systems are located near tectonically active areas, suggesting a link between geothermal activity and the detected anomalies.

3.6 Limitations

While the LOF algorithm provided valuable insights, several limitations were identified:

a. Sensitivity to Parameter Choices: The results heavily depended on the choice of "k" and other hyperparameters.
b. Data Quality: The presence of noise and missing values in the dataset may have influenced anomaly detection accuracy.
c. Interpretability: The unsupervised nature of the algorithm requires significant domain knowledge to interpret anomalies meaningfully.

Integrating data on earthquake precursors such as radon emissions, electric field anomalies, and atmospheric ionization could further enhance the reliability of anomaly detection. Geothermal energy studies indicate the importance of monitoring regions with significant subsurface heat flow, as they often overlap with tectonically active zones【11:11†source】【12:12†source】.

Future research could explore the integration of additional data sources, such as GPS displacement measurements and satellite imagery, to enhance anomaly detection. The combination of unsupervised algorithms like LOF with supervised learning approaches could also improve the interpretability and predictive power of seismic anomaly detection systems. Additionally, leveraging multi-parameter models, including both seismic and geothermal data, could provide a more comprehensive understanding of subsurface dynamics in the Indonesian Ring of Fire.

In summary, the application of the LOF algorithm to Indonesian Ring of Fire seismic data successfully highlighted regions of anomalous seismic activity, contributing to the understanding of tectonic processes in the area. By incorporating insights from earthquake precursor studies and geothermal energy research, this study offers valuable contributions to disaster preparedness and energy resource management in seismically active regions.

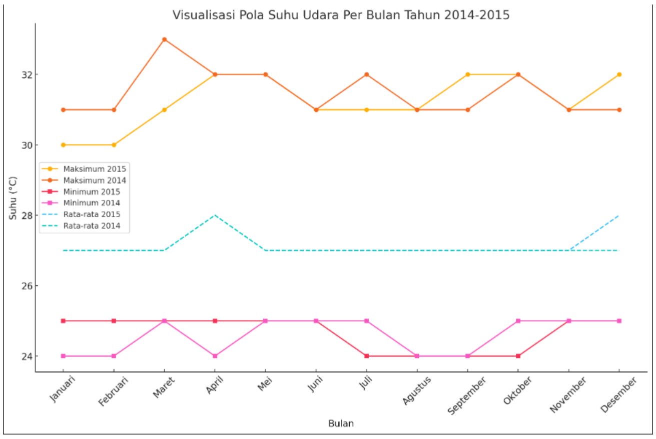

Fig. 1. Display the monthly air temperature data for West Halmahera Regency in 2014 and 2015.

4. CONCLUSION

The study successfully applied the Local Outlier Factor (LOF) algorithm to detect seismic anomalies in the Indonesian Ring of Fire, uncovering clusters of anomalous events that align with known geological and tectonic patterns. By cross-referencing the detected anomalies with earthquake precursors and geothermal observations, the findings reveal a strong correlation between tectonic activity and subsurface thermal variations. This highlights the importance of integrating machine learning techniques with geological and geothermal data to enhance seismic anomaly detection and provide valuable insights into tectonic dynamics.

While the LOF algorithm effectively identified anomalies, challenges such as parameter sensitivity, data quality, and result interpretability remain. Future research should focus on incorporating additional earthquake precursors, satellite imagery, and GPS data to improve anomaly detection and understanding of subsurface processes.

Overall, this study demonstrates the potential of unsupervised machine learning for advancing seismic anomaly detection and contributing to disaster mitigation efforts in tectonically active regions like Indonesia.

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Internet of Things Development for Flood Early Warning Monitoring System: A Review

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ABSTRACT

The purpose of this study is to conduct a systematic literature review. The process of writing a systematic literature review (SLR) is carried out in accordance with this framework. High rainfall during the rainy season can cause continuous rainfall and increase the volume of water that has the potential to cause flooding. Meanwhile, the community does not receive information or notification directly when this happens. To anticipate these problems, it is effective to develop a water level monitoring system as an IoT-based flood early warning tool. This paper is sourced from various publications on IoT-based flood detection systems. This study discusses the definition and selection of methods used in this study, what is the purpose of this study in developing an IoT-based flood detection system, how the results of the flood detection system that has been implemented are compared. In this paper, we present the results of the development of flood detection systems in each previous study. Therefore, the main purpose of this paper is to review research on the development of IoT-based flood detection systems.

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1. INTRODUCTION

Advances in technology and information are bringing major changes in all areas, including the Internet of Things (IoT). With the emergence of the Internet of Things, the number of devices connected to the Internet, from sensors to smartphones, has increased dramatically. The number of these devices is expected to reach approximately 50 billion by 2020. In the age of technology, the use of social media has become increasingly popular among the public. Social media has become a place to interact with others, follow the latest news, and express one's opinions on a particular topic. One of the current concerns is natural disasters in Indonesia. One of the elements developed in the current digital age is the Internet of Things (IoT), or commonly known as the Internet of Things, a concept that aims to extend the benefits of always-on Internet connectivity. To things that can be unique in a web-based architecture and can be described as virtual representations. Floods are the biggest natural disaster problem in Indonesia[1]. Therefore, research in this area will be useful and many researchers have conducted research in this area.

Technological innovations that can be used in floods are flood early warning systems[2]. Residents also need more information about flood detection to help the community be better prepared at any time. The system aims to warn residents so that they are informed in advance of water levels that may cause flooding[3]. On the other hand, for early warnings to prevent significant material and human losses, disaster warning information must be provided to the public quickly and accurately.

2. RESEARCH METHOD

A systematic literature review (SLR) is a systematic and comprehensive method for identifying, evaluating, and synthesizing all relevant research related to a particular topic or research question. The SLR process begins with formulating a clear and focused research question. Researchers then develop specific inclusion and exclusion criteria to determine which studies will be included, taking into account factors such as study design, population, intervention, and desired outcomes. A comprehensive literature search is conducted across multiple databases to collect all relevant studies, both published and unpublished, to minimize potential bias. The identified studies are then reviewed based on specific criteria, and this process typically involves multiple reviewers to ensure objectivity. The SLR method involves several steps, such as those shown in Fig. 1 below:

Fig. 1. SLR steps

2.1 Research Question

Research questions (RQ) are crucial to the systematic literature review (SLR) phase since they aid in defining the study's emphasis, direction, and scope. Researchers can create a thorough synthesis by using research questions as a guide to assess and compile the results of pertinent studies. Some important aspects of research questions in the systematic literature review on IoT-based flood detection systems are as follows:

a. *Determine the methods used (RQ1)*

Understanding and summarizing the approaches taken by different research in developing IoT-based flood detection systems is the goal of this question. This entails recognizing various hardware and software components, communication kinds (such as GSM, Wi-Fi, or other networks), and sensor technologies (such as rain sensors or ultrasonic sensors)[4]. RQ1 aids in highlighting creative and successful methods for creating flood detecting systems.

b. *Research objectives in system development (RQ2)*

RQ2 explores the main research objectives related to the development of IoT-based flood detection systems. This could include objectives such as providing early warning, improving detection reliability and accuracy, or reducing delays in risk notification. By knowing the objectives raised in previous studies, SLR can help identify the main contributions of current research and understand the direction required for system development.

c. *Comparison of results and effectiveness of the system (RQ3)*

This question focuses on comparing the results and effectiveness of the flood detection systems that have been tested and implemented. This includes evaluating the accuracy of the system in detecting potential floods, notification speed, energy efficiency, and accessibility for the community. Through RQ3, researchers can identify the advantages and disadvantages of each system and gain insight into the most appropriate technology and methods.

This research question is important to ensure that the SLR covers key aspects of IoT-based flood detection system development and provides comprehensive guidance for further research as in Table 1 below:

Table 1. PICOC

Population	Early warning system.
Intervention	Flood disaster prediction.
Comparison	Use of sensors and detection systems for flood early warning systems.
Output	Prediction of the accuracy Internet of Things flood early warning systems.
Context	Flood prone environment.

- *RQ 1: How did the authors identify and select the methods used in this study?*
- *RQ 2: What is the purpose of this study in developing an IoT-based flood detection system?*
- *RQ 3: How do the results of the flood detection system that have been carried out compare?*

2.2 Literature Study Research

In the literature search phase of a systematic literature review (SLR), the first step is to identify appropriate keywords and search terms so that the search results are relevant to the research topic. In IoT-based flood detection research, some commonly used keywords include “IoT flood detection system,” “flood early warning system,” “IoT sensor-based flood monitoring,” and flood detection using ultrasonic sensors. Using a combination of these keywords, along with logical operators such as AND, OR, and NOT, helps you narrow or expand your search results as needed. This process is typically done in several academic databases, such as IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and the ACM Digital Library, each of which has its own advantages in providing journals and scientific publications related to the field of technology and the Internet of Things.

The next step is to define inclusion and exclusion criteria that aim to filter out publications that are truly relevant to the research topic. Inclusion criteria may include articles published within the past 5-10 years, research involving experiments or implementation of IoT for flood detection, and studies evaluating the effectiveness of early warning systems. In contrast, exclusion criteria included articles that were merely reviews or non-technical reviews, publications that did not focus on flood detection, and studies that did not have field experiments or real-world applications. Articles that passed the initial screening were then screened by reading the abstracts to assess their relevance to the research objectives, and only relevant articles were read in full. The selected publications were then organized and categorized based on the topic, method, or technology used. For example, articles that focused on the use of ultrasonic sensors could be grouped together, while studies that addressed GSM-based communication technology were placed in another category[5]. This step ensured that the SLR process was carried out systematically and comprehensively, so that all studies relevant to the development of IoT-based flood detection systems could be identified, screened, and produced into a useful and informative summary.

3. DISCUSSION

This article highlights some recent advancements in the application of ultrasonic sensors in Internet of Things-based flood detection systems, based on a thorough analysis of the literature. The analysis's findings demonstrate that ultrasonic sensors can assess water levels accurately and in real time. IoT technology also makes it simple to integrate data with other platforms and enables effective remote monitoring and control.

Table 2. Quality Assessment

QA1	Was the literature created in the last 5 years?
QA2	Is there a method for the literature?
QA3	Does the process of interpreting the results cover all relevant aspects, is efficient and consistent?

The following are the research results from several studies taken as in table 3 below:

Table 3. Result of research

No	Article	Title	RQ1	RQ2	RQ3	QA1	QA2	QA3
1	[6]	Flood warning and monitoring system utilizing internet of things technology	NodeMCU and Blynk, Ultrasonic Sensors	Developing an IoT-based real-time flood monitoring system to provide early warnings	The system can detect water level and rain intensity, and send alerts to users.	Y	Y	Y
2	[7]	Wireless Sensor Nodes for Flood Forecasting using Artificial Neural Network	Wireless Sensor Networks and ANN	Improving flood prediction accuracy using wireless sensor networks and Artificial Neural Network (ANN)	Generate accurate flood predictions for early preventive action.	N	Y	Y
3	[8]	Flood level indicator and risk warning system for remote location monitoring using Flood Observatory System	Wireless Sensor Network	Providing real-time flood warnings to communities in remote areas	The system detects water level and gives a danger warning	N	Y	Y
4	[9]	Flood Monitoring and Early Warning System Using Ultrasonic Sensor	Ultrasonic Sensor	Measuring water levels using ultrasonic sensors to detect potential flooding	The system provides real-time data and warnings to the surrounding community.	N	Y	Y
5	[10]	Flood Detection using Sensor Network and Notification via SMS and Public Network	Sensor Networks and SMS	Sending flood warnings via SMS to users in flood-prone areas	Sends early notification via SMS when water reaches dangerous levels	N	Y	Y
6	[11]	Flash Flood Early Warning System in Colima, Mexico	IoT based on GSM and Satellite Communication	Provides flash flood warnings via GSM and satellite networks	Sending early warnings to mobile devices in affected areas	Y	Y	Y
7	[12]	Low Cost IoT based Flood Monitoring	Machine Learning and IoT Sensors	Using machine learning models to	The system provides machine learning-based	Y	Y	Y

		System Using Machine Learning and Neural Networks		improve the accuracy of flood monitoring and warnings	prediction and warning data.			
8	[13]	Computer Vision and IoT-Based Sensors in Flood Monitoring and Mapping: A Systematic Review	Computer Vision with IoT Sensors	Implementing the Otsu method for flood prediction by analyzing the visual conditions of flood-prone areas.	Flood detection based on visual imagery achieves 94% accuracy in certain areas	Y	Y	Y
9	[14]	Smart IoT Flood Monitoring System	Ultrasonic Sensor and ARM Board	Monitor water levels and control alarm signals and water gates on an IoT-based web server	This real-time system notifies users in high-risk flood areas.	Y	Y	Y
10	[15]	A Review of the Internet of Floods: Near Real-Time Detection of a Flood Event and Its Impact	IoT and SAR sensors	Using satellite SAR data to monitor and classify flood areas in real time	Inundation detection and flood development prediction with satellite data analysis	Y	Y	Y

4. RESULT

This systematic literature review (SLR) on Internet of Things (IoT)-based flood detection aims to understand how these detection systems are developed, tested, and implemented in various studies[16]. Some of the key conclusions drawn from the analysis of the relevant studies are as follows:

a. *Accuracy and Accuracy of Flood Detection*

Most IoT-based flood detection systems use ultrasonic sensors to measure water levels and rain sensors to detect rainfall intensity[17]. These sensors are integrated with microcontrollers such as NodeMCUs to enable real-time data collection and transmission to monitoring centers or mobile applications. The study results show that ultrasonic sensors feature very high accuracy in monitoring water levels, ensuring the reliability of early detection of potential floods[9]. This helps in improving the accuracy of early warning systems, which is very useful for people living in flood-prone areas.

b. *Effectiveness of Early Warning Systems*

In many studies, mobile applications such as Blynk and messaging platforms such as Telegram are used to directly notify users when water reaches a certain level[18]. These app-based systems are very effective in delivering timely notifications as users can receive notifications directly on their smart devices. The app also supports visual monitoring through regularly updated water level charts, allowing users to proactively monitor flood conditions.

c. *Implementation Challenges and System Limitations*

Although IoT technology has shown promising results, there are still many challenges and limitations to overcome. A major challenge faced is the battery life of sensors used in IoT systems, especially in remote areas where access is difficult for replacement or charging. In addition, several studies have shown that the dependency on the Internet or GSM networks hinders the provision of timely warnings, especially in areas where communication networks are unstable. Therefore, further developments in the use of energy-efficient sensors and alternative communication technologies should be considered to increase the robustness and range of the system.

d. Data Integration and Use of Cloud-based Platforms

Most IoT-based flood detection systems integrate data collected from sensors with cloud-based platforms[19]. This integration facilitates access to historical data useful for analysis and long-term decision-making. The results of the study showed that cloud-based platforms not only provide the convenience of real-time case monitoring, but also enable remote monitoring by authorities and the public.

Overall, the results of this discussion indicate that IoT-based flood detection systems have great potential to be implemented as effective and accurate flood early warning solutions[20]. However, further improvements in energy efficiency and network stability are needed to ensure that this system operates optimally under a variety of environmental conditions.

5. CONCLUSION

The preferred spelling of the word "acknowledgment" in America is without an " Flood detection systems using the Internet of Things (IoT) have proven to be effective and efficient in providing early warnings to communities in flood-prone areas. The technology typically uses ultrasonic and rain sensors and allows real-time data collection on water levels and rainfall intensity. Research has shown that integrating IoT with mobile applications such as Blynk and Telegram can provide timely notifications and increase the chances that communities will take preventive measures.

However, there are still some major challenges to overcome, such as relying on battery power for sensors in remote areas and network reliability issues. Solutions to these issues include the use of energy-efficient sensors and the use of alternative, more reliable communication technologies in areas with limited power networks. In addition, the use of cloud platforms in flood detection systems allows better access to remote monitoring and long-term data analysis.

Overall, IoT flood detection systems can be a very useful solution for disaster mitigation. Further improvements in the reliability and scope of this system are expected to provide effective, reliable and widely implemented early warnings, especially in high flood risk areas.

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