Research Article

System for Determining Plant Types Based on Weather Characteristics and Soil pH Using Artificial Intelligence

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Abstract: This research implements the Long Short-Term Memory (LSTM) algorithm for weather forecasting using minimum temperature, maximum temperature, average temperature, air humidity, rainfall, and solar radiation values over the past 30 days. The output consists of forecasts for average temperature, air humidity, rainfall, and solar radiation for the next 30 days. The LSTM model output and soil pH are used to determine plant types using the K-Nearest Neighbor (K-NN) algorithm. Based on the LSTM model testing results, the minimum temperature feature achieved a Mean Absolute Error (MAE) of 0.0078, a maximum temperature of 0.0054, an average temperature of 0.009, air humidity of 0.0099, rainfall of 0.0042, and solar radiation of 0.0208. For the K-NN model, an accuracy of 98% was obtained.

Keywords: k-nearest neighbor, long short-term memory, k-nn model, accuracy, mean absolute error.

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1. Introduction

Indonesia is an agrarian country that relies on the agricultural sector as the main source of livelihood for its people and as a pillar of development. Agriculture is one of the key sectors that serves as an essential resource for society, as the needs derived from agricultural resources are highly complex. These include necessities such as food supply, industrial raw materials, energy sources, and environmental management (Sari, 2021). The agricultural sector plays a crucial role in Indonesia's economic development, although its contribution to the national economy is still lower compared to the oil and gas sector. However, over the past 20 years, agriculture has played a key role in providing food for the majority of the population and has received significant attention from both the government and society. (Purba, et al., 2022). Therefore, agricultural productivity plays an important role in the food supply for society.

Nevertheless, the harvested area of various agricultural commodities in Indonesia has declined, one of which is rice. The total harvested area for rice in 2021 was 10.41 million hectares. Compared to 2020, the harvested area in 2021 decreased from 10.66 million hectares, a reduction of approximately 245.47 thousand hectares or 2.3 percent from the previous year's harvested area. The total rice production in Indonesia in 2021 was around 54.42 million tons of dry grain (GKG), decreasing by 233.91 thousand tons or approximately 0.43 percent compared to the previous year. The total potential failed harvest area for rice in Indonesia also reached 229.38 thousand hectares. Additionally, rice production experienced a significant decline in 2019, with approximately 54,604,033.34 tons per year, down from 59,200,533 tons per year in 2018. Meanwhile, the area of agricultural land planted with crops other than rice showed a sharp increase, reaching 2.09 million hectares by September 2021, before declining again after entering October 2021. (Badan Pusat Statistik, 2022)

On the other hand, massive population growth requires an even higher food supply. According to data from the Central Bureau of Statistics (Badan Pusat Statistik, 2023), Indonesia's population was approximately 264 million in 2018 and increased to 266 million in 2019. In 2020, the population further grew to 269 million. This data indicates a consistent annual increase in population. Based on this data, the ratio of rice production to the population was around 224.08 tons per thousand people in 2018, decreasing to 202.68 tons per thousand people. Therefore, population growth must be balanced with an adequate food supply.

Indonesia has long regarded the agricultural sector as an essential source of income for local households and a significant contributor to much-needed export revenue. Historically, this sector has served as a pillar of Indonesia's economy. However, it can be said that the sector has yet to reach its full potential. Progress in this sector remains hindered by an underdeveloped downstream segment and farmers' inability to meet the growing international demand. Several challenges continue to limit yield improvements, such as inadequate infrastructure and the sector's vulnerability to the dynamic impacts of weather and climate (Wijaya & Susandi, 2018). Climatic factors such as air humidity, sunlight intensity, rainfall, and temperature also play a crucial role in the plant metabolism process (Purba Z., 2018). Poor climate change conditions also impact food security, as climatic factors are fundamental aspects of agricultural production activities that support food security (Budhi, et al., 2022). One of the factors contributing to low agricultural productivity in Indonesia is that the majority of farmers still rely on climate change for farmland management (Prayama, Yolanda, & Pratama, 2018).

The rapid development of technology has brought significant benefits to the agricultural sector. Modernization and the introduction of agricultural technology have increasingly dominated farming activities, especially in rural areas. Agricultural practices have also begun to transform into machine-based and technology-driven practices (Rusdiyana, et al., 2022).

The use of technology in agriculture can be a solution to overcoming climate-related challenges that affect plant growth. One approach is the application of Artificial Intelligence (AI) to determine the optimal plant types based on weather conditions and soil pH at the planting site.

Therefore, in this research, the author proposes the title "Plant Type Determination System Based on Weather Characteristics and Soil pH Using Artificial Intelligence." By utilizing an AI model, predictions can be made through modeling, where sensor data is used as input for the model to determine the optimal plant types based on weather characteristics such as average temperature, minimum temperature, maximum temperature, air humidity, soil moisture, and lighting. This approach can enhance plant productivity and support more precise agriculture. Additionally, climate analysis using artificial neural networks enables more efficient use of agricultural resources.

Moreover, in the development of Agriculture and IoT technology to support Agriculture, advanced Agriculture sensors such as soil pH (J. Zhu et al., 2024), (R. Mary., et.al.2024), (S. R and M. Seenivasan., 2024), and other sensors that are integrated, IoT technology for Agriculture also continues to be developed towards Artificial Intelligence as made by several researchers.(S. Kaur, S. Singh and M. M. Sinha, 2025), (G. A. Mathew, et.al., 2025), (M. Rakib et al., 2024), (R. K and P. R. 2024), (L. Rachakonda and S. Stasiewicz., 2024), (R. Basuel, A. Fajardo and N. D. Perez., 2024).

2. Method

The research method to be used is the Research and Development (R&D) method, which is a development research method that produces products, whether in the form of models, modules, or others, while also assessing the effectiveness of the product. The R&D method can be used by researchers to develop or refine a model (Saputro, 2017).

R&D is a process and set of steps for developing a new product or improving an existing one, whether in the form of hardware or software. In R&D research, model testing is a crucial stage used to assess the feasibility of the developed model. This feasibility includes both process feasibility and outcome feasibility (Zakariah, Afriani, & Zakariah, 2020).

Moreover, the Research Procedure is as follows: The development process diagram in this research consists of six stages: literature study, preparation of tools and materials, development process, and finally, revision. If the revision process runs smoothly without any issues, the process is considered complete. The development procedure can be illustrated as shown in Fig. 1.

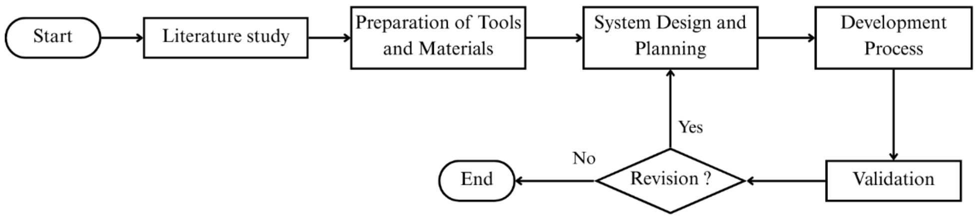


Figure 1. System Development Flowchart

2.1 Literature Study

The literature study is a stage where researchers examine previous studies to gather more information relevant to the research being conducted, namely the plant type determination system based on weather characteristics and soil pH using Artificial Intelligence (AI).

2.2 Preparation of Tools and Materials

The researcher can determine the necessary tools and materials for the study to develop the Plant Type Determination System Based on Weather Characteristics and Soil pH Using Artificial Intelligence.

2.3 System Design and Planning

At this stage, the researcher develops a prototype by creating a preliminary design focused on climate data processing and crop commodity recommendations. The researcher designs a system that explains to users the program structure, data processing, and system architecture to be developed.

The system will be built as an API capable of receiving input in the form of formatted JSON (JavaScript Object Notation) data. This data is then processed using LSTM and K-NN models to generate crop commodity recommendations suitable for the weather conditions at the planting site. The system design flowchart is shown in Fig. 2.

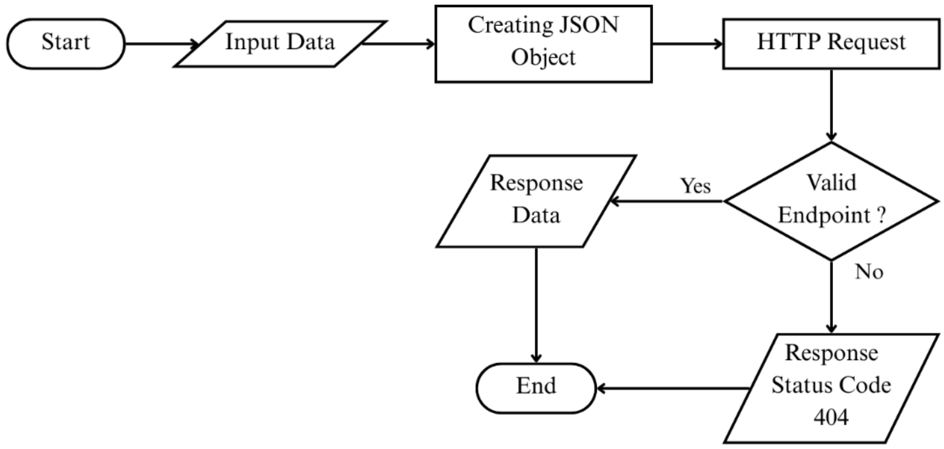


Figure 2. System Design Flowchart

2.4 Development Process

The software development in this research includes the creation of LSTM and K-NN models. The LSTM model is built by training an LSTM neural network using a prepared dataset. The dataset used for model training consists of climate data, including minimum temperature, maximum temperature, average temperature, air humidity, solar radiation, and rainfall. The LSTM model is developed using Google Colaboratory and will later be exported for integration into the website.

The K-NN model is also developed using Google Colaboratory. The dataset used for training consists of plant recommendation data, including temperature, air humidity, soil pH, and rainfall. The K-NN model is trained and developed in Google Colaboratory and will also be exported for use on the website.

2.5 Validation

At this stage, tool validation is conducted to determine whether all components function as expected. Specifically, this process ensures that the developed system can analyze data and provide crop recommendations based on current climate conditions, while also evaluating the performance and efficiency of the system.

3. Result and Analyzes

3.1 Application Programming Interface (API) for Deep Learning Model

This research develops a crop recommendation model by applying deep learning technology and creating an API using Python. The research steps include data preprocessing, Exploratory Data Analysis (EDA), Long Short-Term Memory (LSTM) modeling, K-Nearest Neighbor (K-NN) modeling, and the development of an Application Programming Interface (API) for the deep learning model.

3.1.1 Preprocessing Data

Data preprocessing is a series of steps or processes performed on raw data before it can be used for further analysis or modeling. The purpose of data preprocessing is to clean the data from noise and prepare it for the required analysis and modeling.

3.1.2 Weather Data Preprocessing

In the Daily Weather Dataset of Makassar City, many missing values cannot be used to build an LSTM model. An LSTM model cannot be constructed if there are empty values in the dataset. Additionally, missing values cannot be removed since the data is time series, where maintaining the sequential order is crucial for building the LSTM model. In this dataset, missing values are filled using interpolation. A sample of the preprocessed Daily Weather Dataset of Makassar City can be seen in Table 1.

Table 1. Sample of Preprocessed Daily Weather Dataset

Date	Tn	Tx	Tavg	RH_avg	RR	ss
20-01-2016	25.2	32.2	28	86.5	22.8	7.5
02-01-2017	24.2	32.2	28.4	85	13.5	5
26-01-2018	25.8	32	28	84	9.9	10.5
30-01-2018	26.4	31.2	29	81	2.5	5.8
17-03-2019	25.2	30.4	28.5	82	23.4	2
10-11-2019	26	32.9	29.3	78	4.8	4.7
11-03-2020	26.7	34.5	29.7	77	2	5.1
13-07-2020	25.4	31.8	28	77	1.7	7.6
14-02-2021	25	32.5	26.1	91	19.2	0.3
31-12-2021	25.4	31	26.5	88	1.7	0

Furthermore, in the dataset, Tn represents the minimum temperature, Tx represents the maximum temperature, Tavg represents the average temperature, RH_avg represents the average humidity, and ss represents the rainfall.

3.1.3 Preprocessing of Plant Recommendation Data

In the plant recommendation dataset, there are no missing values, so no preprocessing is required. A sample of the plant recommendation dataset can be seen in Table 2.

Temperature	Humidity	pH	Rainfall	Label
20.87974371	82.00274423	6.502985292	202.9355362	rice
21.14347496	80.33502926	5.594819626	198.6730942	rice
17.02498	16.98861	7.485996	88.55123	snaps
18.86806	15.65809	6.391174	88.51049	snaps
17.13693	20.59542	5.685972	128.2569	red beans
17.13693	20.59542	5.685972	128.2569	red beans
27.43329	87.80508	7.185301	54.73368	green beans
28.17433	81.04555	6.828187	36.35721	green beans
29.4844	63.19915	7.454532	71.89091	black soybeans
34.03619	64.28791	7.741419	66.85511	black soybeans
29.24909	90.06998	6.069172	25.93497	melon
27.76317	90.35568	6.740984	25.21609	melon

Moreover, in the dataset, Tn represents the minimum temperature, Tx represents the maximum temperature, Tavg represents the average temperature, RH_avg represents the average humidity, and ss represents the rainfall.

3.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is the initial process of examining a dataset to understand its characteristics, patterns, and the information it contains. The goal of EDA is to identify the structure, trends, anomalies, relationships between variables, and data distribution within the dataset.

3.2.1 EDA on Weather Dataset

After data processing, descriptive statistics were obtained to describe the characteristics of a dataset for each variable, including minimum temperature (Tn), maximum temperature (Tx), average temperature (Tavg), average air humidity (RH_avg), rainfall (RR), and sunshine duration (ss). The descriptive statistics of the weather dataset are shown in Table 3.

Table 3. Descriptive Statistics of the Daily Weather Dataset

Measurement	**Tn**	**Tx**	**Tavg**	**RH_avg**	**RR**	**ss**
Mean	25,26	32,14	28,13	80,15	10,09	6,5
Std	0,95	1,49	1,06	6,44	21,49	3,26
Min	20	23,2	24,1	52	0	0
Q1	24,8	31,5	27,6	76	0	4,3
Q2 / Median	25,2	32,4	28,2	80	0,6	7,3
Q3	26	33,2	28,8	85	9,6	9,3
Max	29,7	35,8	33,2	97	218,8	11,3

The provided statistics describe the distribution and characteristics of several measurement variables, including Tn (minimum temperature), Tx (maximum temperature), Tavg (average temperature), RH_avg (average air humidity), RR (rainfall), and ss (sunshine duration). To facilitate data understanding, visualization can be performed using a box plot, as shown in Figure 3.

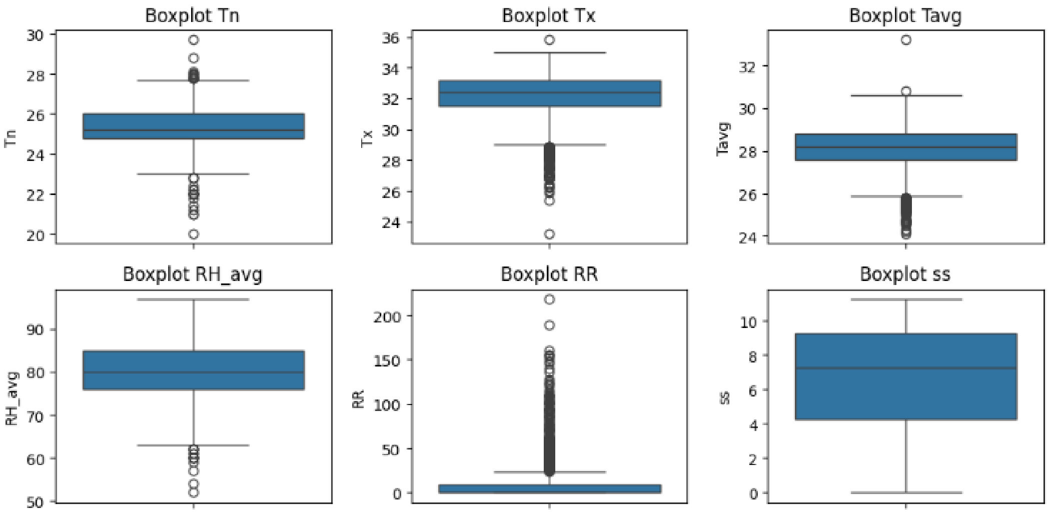


Figure 3. Box Plot of Weather Data Distribution

The data distribution can be visually represented using a histogram, where the histogram divides the range of data values into intervals and then counts the frequency of occurrences in each interval. The histogram of data distribution is shown in Figure 4.

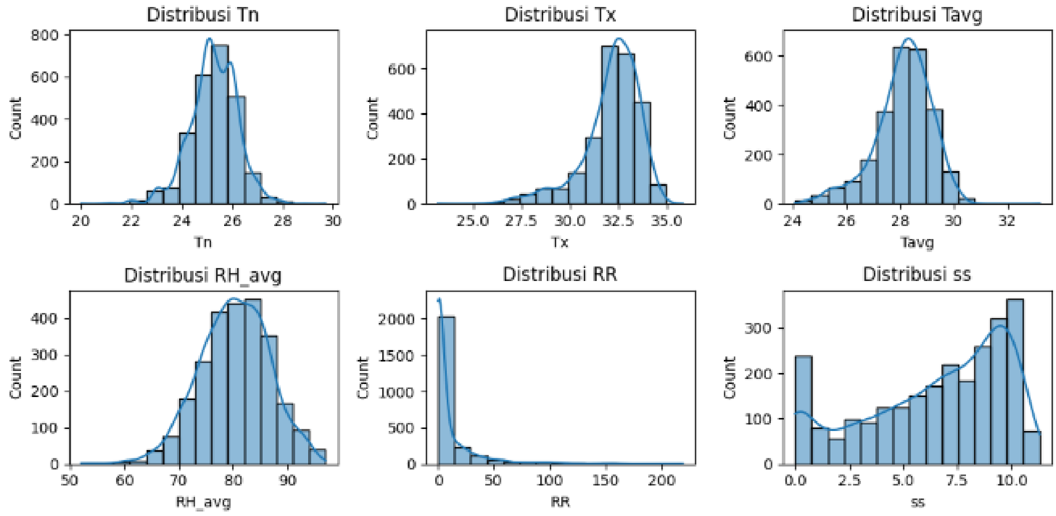
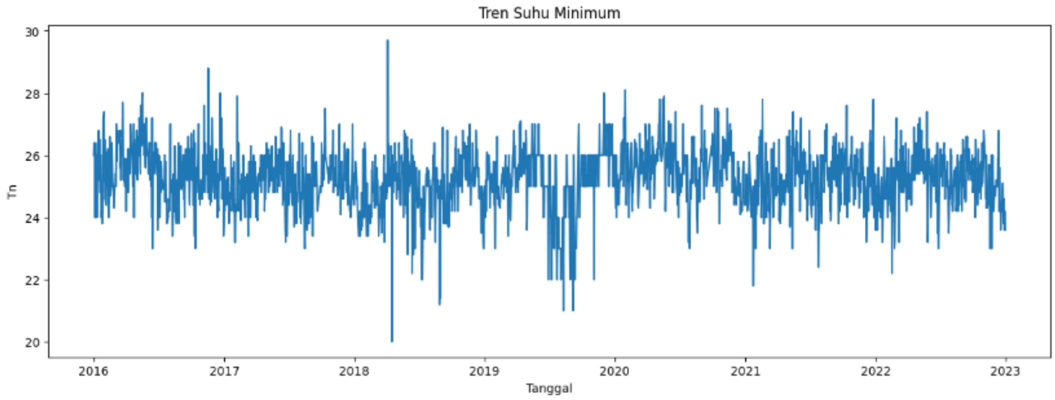
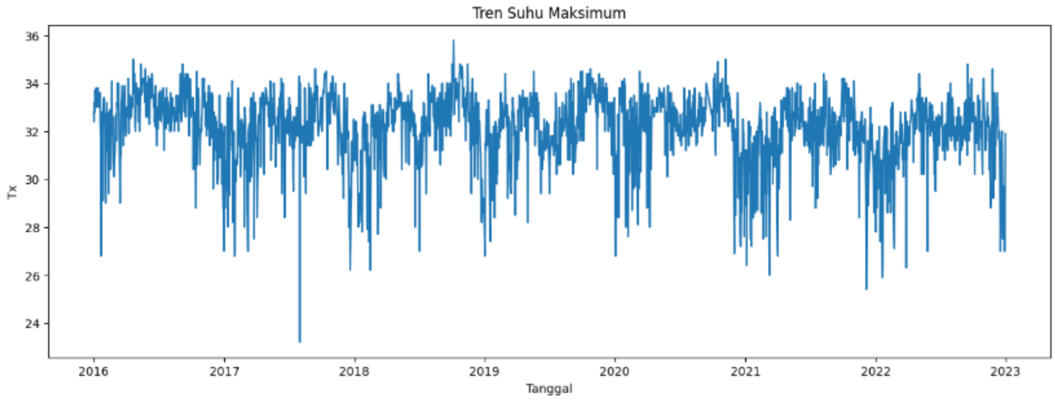


Figure 4. Histogram of Weather Data Distribution

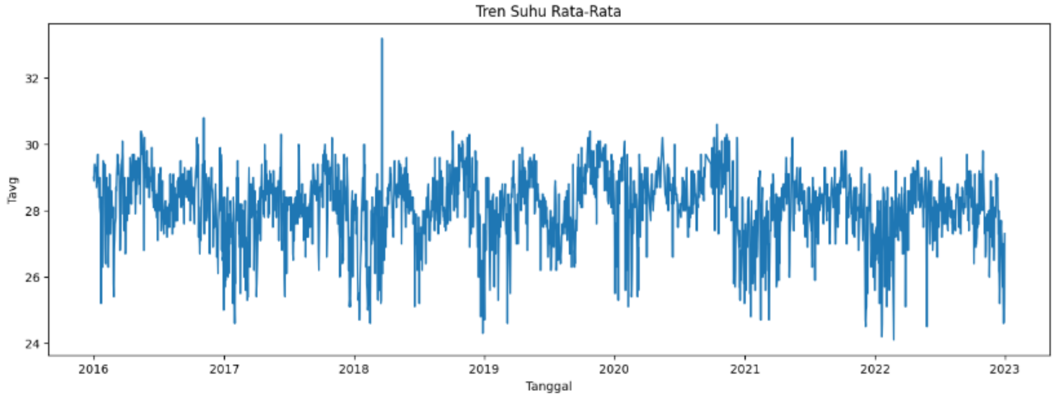
Furthermore, data visualization is performed to identify patterns and trends for each variable. The trend visualization for each variable can be seen in Figure 5.



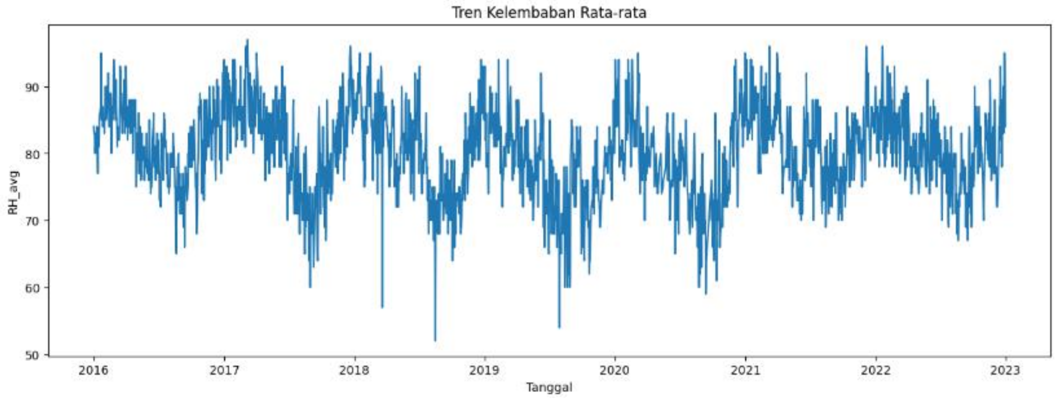
(a)



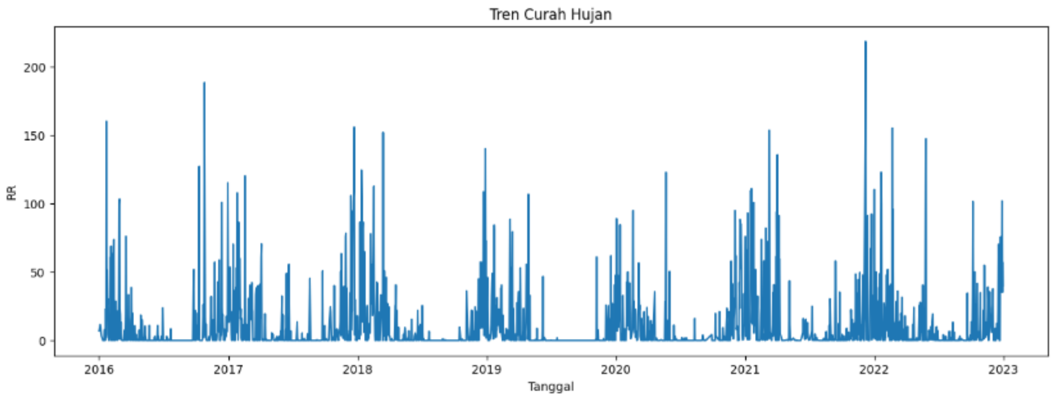
(b)


Tren Suhu Rata-Rata
Tavg
Tanggal

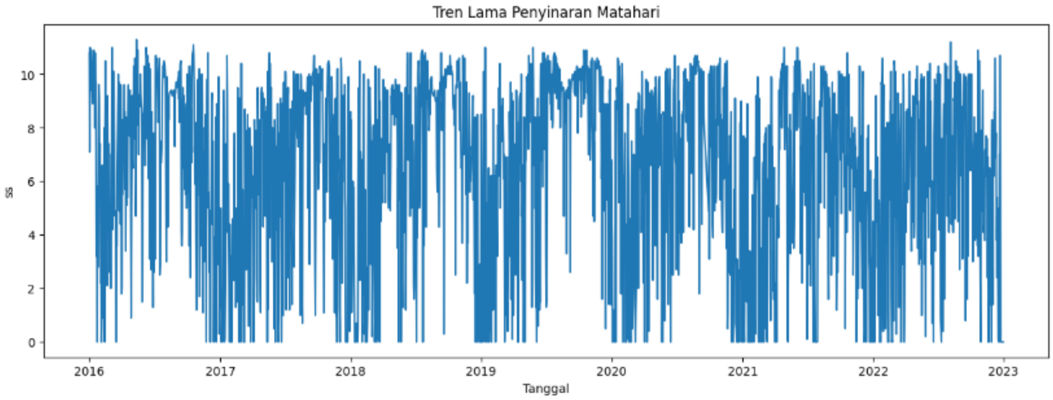
(c)


Tren Kelembaban Rata-rata
RH_avg
Tanggal

(d)


Tren Curah Hujan
RR
Tanggal

(e)



(f)

Figure 5. Weather Data Visualization: (a) Minimum Temperature (b) Maximum Temperature (c) Average Temperature (d) Average Humidity (e) Rainfall (f) Duration of Sunlight

Based on the visualization, we can intuitively recognize patterns, changes, or trends in the dataset. With the x-axis representing time and the y-axis representing variable values, we can observe changes in variable values over each period. Through these graphs, we can identify increases, decreases, or fluctuations in the time series data.

3.2.2 EDA on the Plant Dataset

After data processing, descriptive statistics were obtained to describe the characteristics of a dataset for each variable. The descriptive statistics of the plant dataset are shown in Table 4.

Table 4. Descriptive Statistics of the Plant Recommendation Dataset

Measurement	**Temperature**	**Humidity**	**Soil pH**	**Rainfall**
Mean	24,97	60,62	6,62	93,86
Std	4,74	30,52	0,73	70,88
Min	15,33	14,26	5,01	20,21
Q1	20,4	21,35	6,09	49,07
Q2 / Median	26.44	74,5	6,57	70,69
Q3	28,78	85,94	7,11	107,39
Max	34,95	94,96	8,87	298,56

The provided statistics describe the distribution and characteristics of several measurement variables, including temperature, air humidity, soil pH, and rainfall. To facilitate data comprehension, visualization can be performed using a histogram to observe the data distribution in the dataset based on its features, as shown in Figure 6.

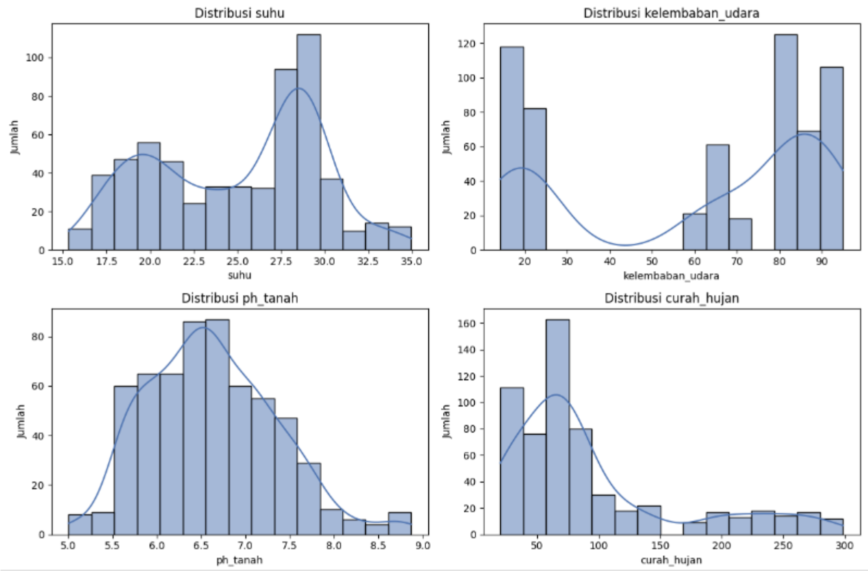


Figure 6. Histogram of Plant Dataset Distribution Based on Features

The histogram shows the data distribution based on temperature, air humidity, soil pH, and rainfall features from all the data in the dataset. Meanwhile, the data distribution based on plant labels is shown in Figure 7.

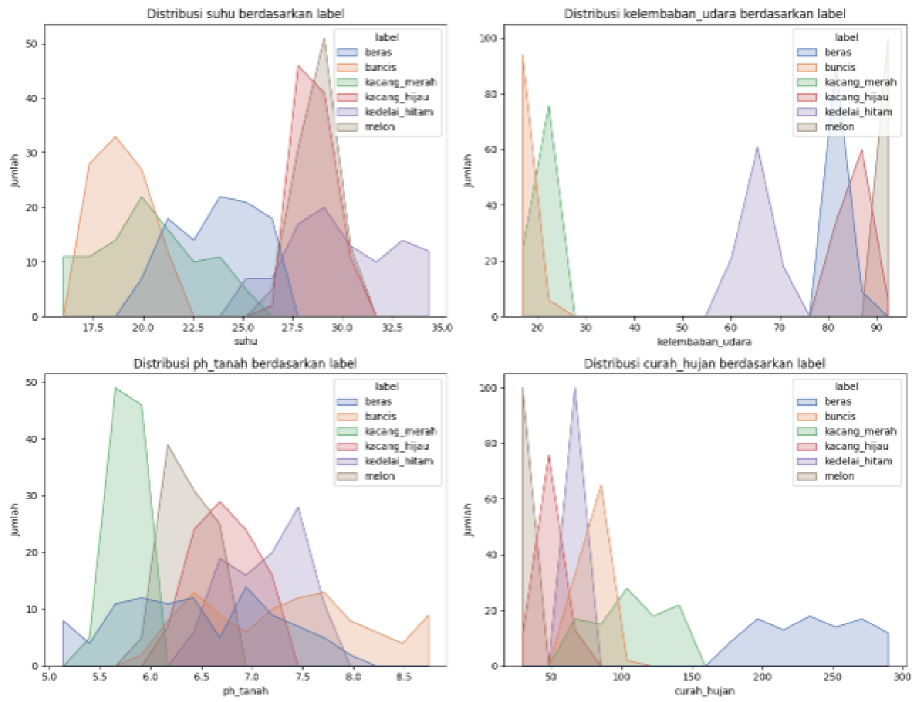


Figure 7. Data Distribution Based on Plant Labels

Statistics describing the distribution and characteristics of each feature, including temperature, air humidity, soil pH, and rainfall for each plant label, can be visualized using a box plot, as shown in Figure 8.

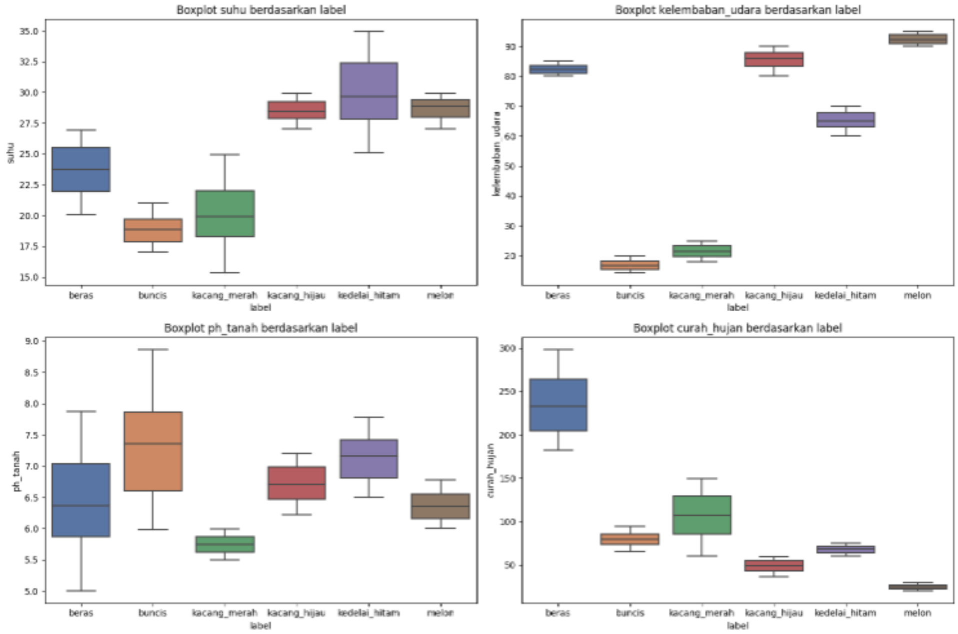


Figure 8. Box Plot of Features Based on Plant Labels

3.3 Long Short-Term Memory (LSTM) Modelling

The development of the LSTM model is carried out to generate a weather prediction model for the future. The process of building the LSTM model can be done through the following steps.

3.3.1 Data Preparation

This stage involves reading the weather dataset into a data frame. The data is separated into features and labels, followed by data normalization. Data normalization is a process used to eliminate unstructured data and redundancy. Min-max normalization is one approach to data normalization, aiming to transform values in the dataset into a range between 0 and 1. Before training the LSTM model, the dataset needs to be split into 80% training data and 20% testing data.

3.3.2 Sequence Creation

A sequence is a series of data provided to the LSTM model for processing and training. The input data is arranged in order before being fed into the LSTM model. Each element in this sequence has a relationship or dependency on both the previous and subsequent elements. A simple illustration of the sequence is shown in Table 5.

Table 5. Sequence Illustration

X	**y**
$\mathbf{x_1, x_2, x_3, \ldots, x_{30}}$	$x_{31}, x_{32}, x_{33}, \ldots, x_{60}$
$\mathbf{x_2, x_3, x_4, \ldots, x_{31}}$	$x_{32}, x_{33}, x_{34}, \ldots, x_{61}$
$\mathbf{x_3, x_4, x_5, \ldots, x_{32}}$	$x_{33}, x_{34}, x_{35}, \ldots, x_{62}$
$\vdots$	$\vdots$
$\mathbf{x_n, x_{n+1}, x_{n+2}, \ldots, x_{n+29}}$	$x_{n+30}, x_{n+31}, x_{32}, \ldots, x_{n+59}$

3.4 LSTM Model Training

The LSTM formula is divided into four parts, as follows:

a. *Forget Gate*

$$f_t = \sigma(W_{f_x}x_t + W_{f_h}h_{t-1} + W_{f_c}c_{t-1} + b_f)$$

b. *Input Gate*

$$i_t = \sigma(W_{i_x}x_t + W_{i_h}h_{t-1} + W_{i_c}c_{t-1} + b_i)$$

c. *Memory Update*

$$c_t = f_t \circ c_{t-1} + i_t \circ \emptyset(W_{c_x}x_t + W_{c_h}h_{t-1} + b_c)$$

d. *Output Gate*

$$o_t = \sigma(W_{o_x}x_t + W_{o_h}h_{t-1} + W_{o_c}c_t + b_o)$$

$$h_t = o_t \circ \emptyset(c_t)$$

Where x_t is the input vector, c_t is the memory of the current block, c_{t-1} is the memory of the previous block, h_t is the output of the current block, h_{t-1} is the output of the previous block, and W is the weight matrix.

This stage requires the determination of the model to be formed based on the selected parameters. The parameters used in the LSTM architecture for each feature are shown in Table 6.

Table 6 LSTM Architecture

Feature	Hidden Layer	Neuron Unit	Epoch
Tn	2	128, 64	1000
Tx	2	128, 64	1000
Tavg	2	128, 64	1000
RH_avg	2	128, 64	1000
RR	2	128, 64	1000
ss	2	64, 64	2000

3.5 LSTM Model Evaluation

The evaluation matrix used for the model is MAE (Mean Absolute Error). MAE measures the absolute difference between the actual and predicted values. MAE provides an overview of how accurate the model is in making predictions on the data. The MAE obtained from the model training process is shown in Table 7.

Table 7. LSTM Model Training Evaluation

Output Feature	MAE
Tn (Minimum Temperature)	0.0078
Tx (Maximum Temperature)	0.0054
Tavg (Average Temperature)	0.0090
RH_avg (Average Humidity)	0.0099
RR (Rainfall)	0.0042
SS (Duration of Sunlight)	0.0208

3.6 K-Nearest Neighbor (K-NN) Modelling

Creating the K-NN model is done to generate a plant recommendation model. The process of creating the K-NN model can be carried out through several steps as follows.

3.7 Data Preparation

This stage is where the plant dataset will be read, and the data will be separated into features and labels. Before training the K-NN model, the dataset needs to be divided into 80% training data and 20% testing data.

3.8 K-NN Model Training

The classification equation using K-NN is as follows equation 1.

$$d_i = \sqrt{\sum_{i=1}^{n}(y_i - x_i)^2} \quad (1)$$

Where d_i represents the proximity distance, x_i is the training data, y_i is the testing data, n is the data dimension, and i is the data variable.

The model training stage is performed to build the K-NN model so that it can provide plant recommendations. The value of the nearest neighbors (k) set for the K-NN model to be built is 5.

3.9 K-NN Model Evaluation

After building the K-NN model, the model is evaluated to determine the accuracy of the built model. The evaluation is done by calculating the percentage of data correctly predicted out of the total data. Based on the model evaluation results using testing data, an accuracy of 98% was obtained. The prediction results from the model are shown in Table 8.

Table 8 K-NN Model Prediction Results

Prediction Results	**Total**
True	118
False	2

3.10 Creation of Application Programming Interface (API)

The creation of an API-based system needs to have a standard. In determining the data transfer method for the API, the author uses the REST architecture style, which utilizes HTTP verbs to interpret a command.

3.11 Creation of API for Weather Prediction Model

The process of creating the API aims to retrieve the URL data from the LSTM model that has been built. This LSTM model will then be used to predict the weather for the next 30 days.

The weather prediction using the LSTM model uses input in the form of data from the previous 30 days. Therefore, the request to the API will return the URL of the model that has been created, as it is not feasible to use query parameters if the data being sent is too large. A request to the /weather API will require a query parameter, which is the feature, to determine which feature will be predicted. The values that can be used for the query parameter feature are shown in Table 9.

Table 9. Query Parameter Feature for Weather Prediction API Request

Value	**Explanation**
Tn	Model for minimum temperature prediction
Tx	Model for maximum temperature prediction
Tavg	Model for average temperature prediction
RH_avg	Model for average humidity prediction
RR	Model for rainfall prediction
ss	Model for sunshine duration prediction

Moreover, to request the API, here is the URL with the required query parameters. The weather Prediction API Request URL is as follows: https://my-api.com/weather?feature=Tn. The request will return a response in the form of the URL of the LSTM model for prediction based on the feature sent in the query parameter. Below is the response from the Weather Prediction API. In addition, the Response program script of the Weather Prediction API is shown as the following program script:

```
{
  "feature": "Suhu Minimum",
  "feature_code": "Tn",
  "model":
"https://greenjs.netlify.app/api/models/lstm/Tn/model.json"
}
```

Next, the model is ready to be used for prediction by utilizing the TensorFlow library. To make predictions using the model that has been created, here is an example of the program.

```
import "https://cdn.jsdelivr.net/npm/@tensorflow/tfjs";
async function loadModel(url) {
  const loadedModel = await tf.loadLayersModel(url);
  return loadedModel;
}
fetch("https://my-api.com/weather?feature=Tn")
  .then((response) => {
    return response.json();
  })
  .then((response) => {
    loadModel(response.model).then((loadedModel) => {
      const model = loadedModel;
      const inputTensor = tf.tensor3d([input]);
      let predictions = model.predict(inputTensor)
                             .dataSync();
      console.log(predictions);
    });
```

```
  });
------------- Script Weather Prediction Program Using LSTM Model ----------
```

In the program, the input variable is the variable that holds the values in the form of an object that will be processed by the LSTM model. The input variable contains an object with a length of 30, which means it holds data from the previous 30 days, with each property being minimum temperature, maximum temperature, average temperature, humidity, rainfall, and sunlight radiation. Here is an example of an object that can be used as input to the model.

```
let input = [
  {
    suhu_minimum: 23,
    suhu_maksimum: 30,
    suhu_rata_rata: 27,
    kelembaban_udara: 66,
    curah_hujan: 10,
    penyinaran_matahari: 4
  },
  // dan seterusnya hingga 30 data
];
       ------- Script Weather Prediction Input Object ------
```

The prediction results from the model are in the form of an array with a dimension of 30, where the array contains the predicted results for the next 30 days. An example of the prediction results from the model is shown in this output i.e. Response of Weather Prediction Results Using the LSTM Model.

```
0: 25.418731689453125
1: 26.01695823669434
2: 25.07781028747558
3: 26.24836826324725
4: 24.93085670471191
5: 25.974849700927734
6: 25.419947509765625
7: 25.244007873535156
8: 27.297595977783203
9: 26.236707687377793
10: 25.721935846958477
11: 26.6845569610957
12: 25.262585809975562
13: 25.54388046264648
14: 24.961297988891602
15: 25.82990938720703
16: 24.41254808518554
17: 25.28297996520996
18: 24.9453111817086
19: 25.45417538944824
20: 25.278285980224
21: 25.25286483764648
22: 25.245882171767578
23: 25.28408583071093
24: 25.38872528076172
25: 24.08146858215332
```

```
26: 24.9838983921425
27: 22.762016296386
28: 26.167541598390625
29: 21.83373260498047
```

3.12 Creation of Plant Recommendation API

The process of creating the plant recommendation API aims to provide plant recommendations using the K-NN model that has been created. The plant recommendation API accepts a query parameter called 'data' that holds values in the form of an object to be processed by the K-NN model. The data object has properties such as temperature, humidity, soil pH, and rainfall. Encoding is then performed so that the data object can be loaded through the URL. Below is an example of the program for requesting the plant recommendation API. The following is the Plant Recommendation API Request Script.

```
let data = {
  suhu: 30,
  kelembaban_udara: 90,
  ph_tanah: 30,
  curah_hujan: 88,
};

data = encodeURIComponent(JSON.stringify(data));

fetch("https://my-api.com/plant?data=" + data)
  .then((response) => response.json())
  .then((responseData) => {
    console.log(responseData);
  });
```

The plant recommendation API request will return a JSON response containing plant recommendations based on the features sent in the query parameter data. The response is a JSON object that includes an array of recommended plants, which are the result of data processing using the K-NN algorithm. The response from the factory recommendation API request is shown in this script, Response from Factory Recommendation API.

```
{
  "rekomendasi_tanaman": [
    "kedelai_hitam",
    "kacang_hijau",
    "melon",
    "kacang_merah",
    "buncis",
    "beras"
  ]
}
```

4. Conclusion

Based on the research results, several conclusions can be drawn as follows: From the results of training the model using the LSTM algorithm for weather forecasting, the error with MAE values for each feature is 0.0078 for the minimum temperature feature, 0.0054 for the maximum temperature feature, 0.0090 for the average temperature feature, 0.0099 for the humidity feature, 0.0042 for the rainfall feature, and 0.0208 for the sunlight radiation feature. From the test results, the system can determine the optimal plant species using the K-NN algorithm, achieving an accuracy of 98%, where 118 data points were classified correctly and 2 data points were classified incorrectly. The implementation of the API for the weather prediction model and plant species determination was successfully applied using the REST architecture.

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