byAccredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 7 No. 1 (2023) 1363 - 1370 ISSN Media Electronic: 2580-0760

Predicting the Planting Time of Bird's Eye Chili Based on Environmental Conditions Using Internet of Things (IoT) and Neural Network Method

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Abstract

In Indonesian cuisine, Red Tabasco pepper holds a significant place as a commonly used ingredient. However, the cultivation of this chili variety is not without its challenges, primarily due to the volatile nature of chili prices. Farmers often grapple with the critical decision of when to plant Tabasco pepper to optimize their yields and income. Understanding the complexities of this decision-making process in the context of varying environmental conditions is crucial. Thanks to recent advancements in Internet of Things (IoT) technology, innovative systems have emerged to address these challenges.This study delves into the development of an IoT-based solution aimed at assisting farmers in precisely determining the optimal planting time for Tabasco pepper. It leverages five key criteria—average temperature (°C), average humidity (%), rainfall (mm), length of sunlight (hours), and groundwater usage data (m3)—to make data-driven planting decisions. The pressing need for such a system becomes evident when considering the unpredictability of climate patterns and their direct impact on crop outcomes. Utilizing historical data from 2019, obtained from the DKI Jakarta Provincial Government Open Data, and climate data from the Meteorological Agency, Climatology, and Geophysics (BMKG), the authors have successfully developed an IoT-based prototype. This prototype employs a neural network algorithm to analyze the aforementioned criteria. The outcome is a reliable prediction system that boasts an impressive accuracy rate of 91.26%. By offering this level of precision in determining the ideal planting time for Tabasco pepper, the system extends invaluable support to farmers, helping them optimize their cultivation practices and navigate the uncertainties of the chili market.

Keywords: *Red Tabasco pepper, neural network, planting time, prediction*

1. Introduction

The planting season is a critical period for farmers, where the precise timing of crop cultivation can make the difference between bountiful harvests and disappointing yields. In recent years, the impacts of climate change have further heightened the importance of adhering to the right planting season, as deviation from optimal conditions can result in subpar plant growth [1], [2]. Such deviations not only jeopardize crop productivity but also disrupt market dynamics, potentially leading to suboptimal pricing upon harvest [3]. Amidst this backdrop, the significance of accurate planting time prediction cannot be overstated.

In the context of Indonesia's culinary landscape, Tabasco pepper (Capsicum frutescens) holds a prominent place as a widely used cooking spice[4]. Yet, the cultivation of Tabasco pepper is far from straightforward, primarily due to its susceptibility to environmental conditions. The fruit's small size, measuring 2-3.5 cm in length and 0.4-0.7 cm in diameter, makes it particularly sensitive to climate variations. Typically taking 2.5-3 months to bear fruit and continuing to produce over a harvest period of six months or more, Tabasco pepper plants can thrive for up to 24 months with multiple harvesting cycles[5]. To unlock its full potential, farmers must meticulously consider various environmental criteria.

This study seeks to revolutionize Tabasco pepper farming by harnessing the power of predictive technology. By incorporating crucial environmental factors such as average temperature (°C), average humidity (%), rainfall (mm), length of sunshine (hours), and groundwater usage (m3) into a neural network algorithm, the authors aim to develop a robust predictive model. The ultimate goal is to provide Tabasco pepper farmers with accurate and reliable information regarding the optimal planting time [6].

Accepted: 24-06-2023 | Received in revised: 21-12-2023 | Published: 26-12-2023

While prior research has explored prediction models for chili planting times, including those using algorithms like C45 and simple linear regression [2], [4] ,[7] these models have displayed limitations in achieving optimal accuracy. Neural networks, particularly the Neural Network (NN) algorithm, offer a promising alternative due to their reputation for delivering rapid and precise predictions [8]. Their ability to handle complex, nonlinear relationships makes them well-suited for modeling the intricate interplay of environmental factors in planting time predictions [9], [10]

In light of these considerations, this research endeavours to create an artificial neural network model specifically tailored to address the challenge of predicting the optimal planting time for Tabasco pepper. By doing so, it aims to equip Tabasco pepper farmers with a reliable reference tool that empowers them to make informed decisions about when to commence planting, thus mitigating risks and maximizing yields in the face of ever-changing environmental conditions. This endeavor holds the potential to not only transform the agricultural practices of Tabasco pepper farming but also contribute significantly to the agricultural sector's resilience in the face of climate variability.

2. Research Methods

2.1 Design

While the proposed conceptual design has not yet undergone field testing, the authors are diligently preparing for a rigorous testing and validation phase to ensure its practical viability and effectiveness [11]. The envisioned testing procedures will play a pivotal role in refining the system's performance and reliability.

The planned testing and validation procedures encompass several key components:

Sensor Network Deployment: Multiple sensors, strategically positioned within the Tabasco pepper cultivation area, will continuously collect data on environmental factors such as temperature, humidity, rainfall, sunlight duration, and groundwater usage [12]-[14]. This network of sensors will be meticulously calibrated and synchronized to ensure data accuracy.

Data Collection: The sensor network will continuously transmit data to a centralized cloud database in real-time. Additionally, periodic data collection will capture variations over time, enabling a comprehensive understanding of environmental trends.

Algorithm Validation: The neural network algorithm, the core of the predictive model, will be subjected to rigorous validation. Historical data from 2019, obtained from the DKI Jakarta Provincial Government Open Data, and climate data from the Meteorological Agency, Climatology, and Geophysics (BMKG), will be utilized for this purpose. The performance of the algorithm will be assessed through cross-validation and benchmarking against existing models.

Model Calibration: As part of the validation process, the model's parameters will be fine-tuned to optimize predictive accuracy. This step is critical in ensuring that the model provides reliable planting time recommendations.

Field Trials: Field trials will be conducted in collaboration with local Tabasco pepper farmers. The system's predictions will be put to the test in real-world cultivation scenarios. Data collected during these trials will serve as a crucial benchmark for evaluating the model's practical utility.

Accuracy Assessment: The accuracy of the predictive model will be rigorously assessed by comparing its recommendations with the actual planting times and crop yields observed during field trials. Statistical measures such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) will be employed to quantify the model's performance.

User Feedback: Farmer input and feedback will be actively solicited and incorporated into system improvements. This iterative process will enhance the model's user-friendliness and practical relevance.

Scalability and Generalization: The testing phase will also explore the system's scalability and generalization to different geographic regions and environmental conditions, ensuring its applicability beyond the initial testing area.

Documentation and Guidelines: Throughout the testing and validation process, comprehensive documentation will be generated to guide potential users in replicating the system for their specific agricultural applications. Clear guidelines will be provided to facilitate successful implementation.

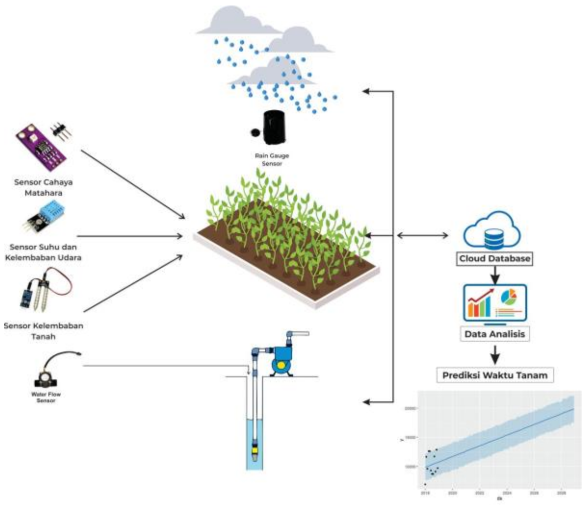

Figure 1. Design of the sensor that predicts the planting time of Tobasco pepper based on environmental conditions.

DOI: https://doi.org/10.29207/resti.v7i6.5199

By subjecting the proposed system to these rigorous testing and validation procedures, the authors aim to instill confidence in its practicality, reliability, and effectiveness. This robust evaluation process will not only refine the system's performance but also pave the way for its seamless integration into Tabasco pepper farming practices, ultimately benefiting farmers and the agricultural sector. Desain conceptual as a whole as depicted in Figure 1.

2.2 Prototype

The research prototype comprises three parts, and the first part is dedicated to the rainfall sensor, as illustrated in Figure 2.

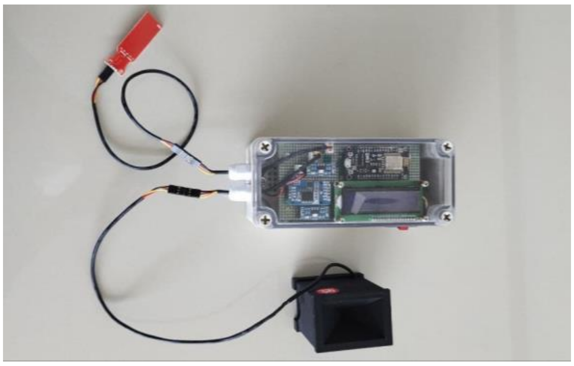

Figure 2. prototype of rainfall sensor

Part 2 of the prototype involves a water flow sensor, which is utilized to measure and calculate the daily groundwater usage within the chili planting time prediction system, as demonstrated in Figure 3.

Figure 3. prototype of water flow sensor

The third part of this system encompasses three sensors: a temperature sensor, an air humidity sensor, and sun light sensor, as depicted in Figure 4.

The collected data from the developed prototype will be utilized within an IoT system to predict the optimal planting time for Tabasco pepper based on environmental conditions. To create the desired prediction model, the authors gather datasets from diverse sources. These datasets are then used as experimental inputs for the model development, aligned with the parameters collected through the sensors operating within the system.

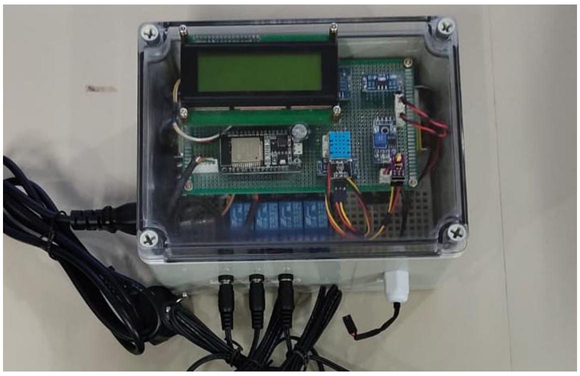

Figure 4. Prototypes of temperature sensor, air humidity sensor, and sun light sensor

2.3 Data

Collecting data on the criteria for growing good chili peppers is paramount to the success of this study as it forms the foundation upon which the predictive model is built. These data points serve as vital indicators of the environmental conditions necessary for optimal Tabasco pepper cultivation.

Temperature: The specific temperature ranges, with daytime temperatures between 25-27 degrees Celsius and nighttime temperatures between 18-20 degrees Celsius, are critical because they directly influence the growth and development of Tabasco pepper plants. Deviations from these ranges can have a substantial impact on crop yield and quality.

Rainfall: The monthly rainfall range of 100-200mm [4] is a pivotal factor as it dictates the water supply available to the plants. Adequate moisture is essential for healthy growth, and deviations from this range can lead to water stress or disease susceptibility.

Humidity: Maintaining humidity within the range of 60-80% is vital for Tabasco pepper plants[2]. High humidity levels can render the plants vulnerable to diseases, emphasizing the importance of this criterion in ensuring a disease-free crop.

Sunlight: The requirement of 6-8 hours of full sunlight per day [4] is indispensable as insufficient sunlight can result in abnormal growth patterns and reduced yields. This criterion underscores the significance of providing Tabasco pepper plants with optimal lighting conditions.

Groundwater Usage: The data on groundwater usage obtained from the DKI Jakarta Provincial Government Open Data portal [6] is an essential component, as it reflects the availability of a critical water resource. Planting Tabasco peppers when groundwater demand is low helps prevent resource depletion and ensures sustainable cultivation practices.

DOI: https://doi.org/10.29207/resti.v7i6.5199

Incorporating these data points into the predictive model allows for a holistic assessment of the environmental conditions necessary for successful Tabasco pepper farming. By aligning the model's recommendations with these criteria, farmers can make informed decisions about the ideal planting time, ultimately enhancing crop yield and quality. Therefore, the collection and utilization of such data are pivotal to the research's goal of supporting Tabasco pepper farmers in their cultivation efforts.

From these 5 criteria, historical data for 2018 with a total of 365 days in 2018 from several dataset sources were collected, including groundwater use data from the DKI Jakarta Provincial Government Open Data Portal and rainfall data used as supporting data. obtained from the Meteorology, Climatology and Geophysics Agency (BMKG), with the labels: Tavg: Average temperature (°C); RH_avg: Average humidity (%); RR: Rainfall (mm); ss: Duration of sunlight (hours); pat: Groundwater usage (m3); and Predik: Predicted planting time (1/0).

2.4 Research Procedures

The research encompasses four distinct phases: 1) data collection, 2) preprocessing, and 3) model development, 4) followed by the validation of results, as depicted in Figure 5.

Data Collection: In this initial phase, the research team gathers the necessary data for the study. This data could come from various sources such as surveys, experiments, existing datasets, or any other relevant data repositories. The data collected should be pertinent to the research objectives and hypotheses. The research team ensures the data's accuracy, relevance, and completeness during this phase.

Preprocessing: Once the data is collected, it often requires cleaning and preparation before it can be used for analysis. Data preprocessing involves tasks such as data cleaning (removing errors or inconsistencies), data transformation (e.g., normalization or scaling), and feature selection or extraction to enhance the data's quality and suitability for analysis. This phase is crucial for ensuring the data is in a usable state for subsequent analysis.

Model Development: In this phase, the researchers work on developing models or analytical approaches to answer the research questions. The choice of models and methods depends on the nature of the research, but it often includes statistical analyses, machine learning algorithms, or other analytical tools. Researchers fine-tune and validate these models to ensure they are appropriate for the research goals.

Validation of Results: After the models are developed and analyses are conducted, the next step is to validate the results. This typically involves assessing the robustness and reliability of the findings. Researchers may employ various validation techniques, such as cross-validation, hypothesis testing, or peer review, to confirm the validity of their results. This phase ensures that the research outcomes are credible and can be relied upon for drawing meaningful conclusions.

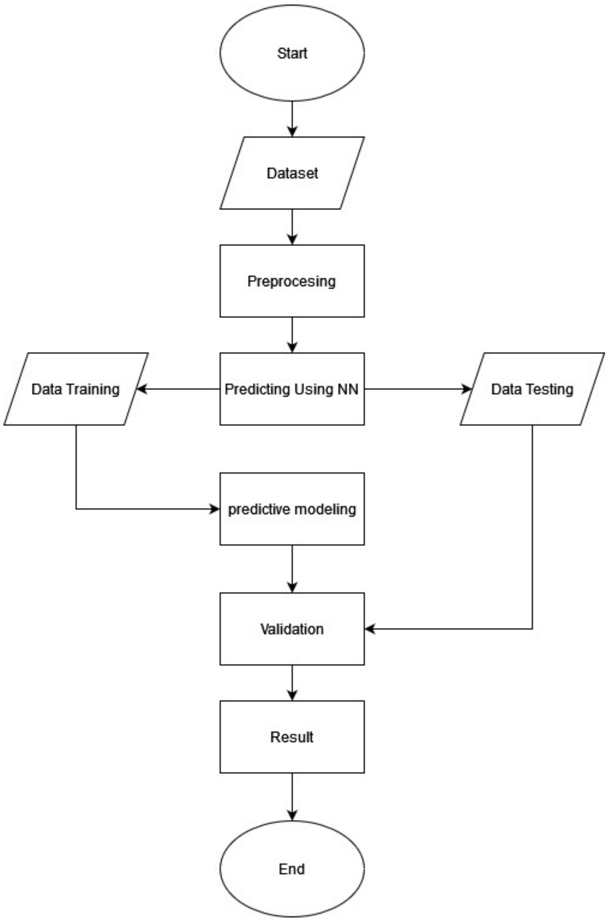

Figure 5. Research Procedure

Each phase contributes to the overall success and reliability of the research, ultimately leading to sound conclusions and insights.

In the initial phase, one year's worth of climate conditions and groundwater usage data were obtained from the DKI Jakarta Provincial Government Open Data Portal and BMKG. These datasets were merged into a single file, which was subsequently divided into training data comprising 183 entries and testing data consisting of 182 entries. Figure 6 illustrates the dataset structure, encompassing five variables.

Data Preprocessing:

Merging Datasets: The climate conditions and groundwater usage datasets were merged into a single file, facilitating a unified and comprehensive analysis.

Handling Missing Values: Missing data points, if any, were meticulously addressed using appropriate techniques. These may include imputation methods,

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such as mean or median replacement, or more advanced methods like regression imputation, depending on the nature and extent of missingness.

Outlier Detection and Handling: Outliers, if present, were identified and addressed. Extreme data points that could skew the predictive model were either corrected or removed to maintain data integrity.

Normalization and Scaling: To ensure that all variables are on a consistent scale, normalization and scaling techniques were applied where necessary. This step aids in preventing certain variables from dominating the model solely due to their larger numerical ranges.

Data Split: The preprocessed dataset was divided into two subsets: a training dataset comprising 183 entries and a testing dataset consisting of 182 entries. This partitioning is essential for model development and evaluation.

Table 1. Dataset Collection Process

No	Tavg	RH_avg	RR	ss	pat
1	26.8	90	145.3	4.5	19852.62
2	27.6	80	58.8	0	20908.74
3	28.5	77	0	3	21930.79
4	28.3	82	2.5	0	21964.86
5	27.9	85	0.2	0.4	21998.93
6	27	87	18.2	0	22033
7	26.9	89	15	1.2	22067.07
8	28.2	80	2.8	2.5	22101.13
9	27.7	85	28.7	0	22135.2
10	25.9	90	23.6	0	22169.27

The dataset structure, as illustrated in Table 1, encompasses five key variables, namely average temperature (°C), average humidity (%), rainfall (mm), length of sunshine (hours), and groundwater usage (m3). These variables were subjected to the aforementioned preprocessing steps to ensure their quality and compatibility with the subsequent neural network model development.

By meticulously handling missing values, outliers, and standardizing variables through normalization and scaling, the preprocessing stage aims to prepare the dataset for accurate and reliable model training. These steps are crucial in ensuring the robustness and effectiveness of the predictive model developed in the subsequent phases of the research.

2.5 Neural Network

A neural network helps machines learn patterns by themselves, saving data scientists from repeatedly giving commands for new patterns. It's called "neural" because it works somewhat like the human brain, with nodes akin to brain cells. These nodes are all interconnected [15]. Neural networks use math formulas to process input data and come in various types, including single, double, or multi-layer networks, categorized by the number of layers. They can also be grouped by data flow direction. In a feed-forward network, information goes one way, from input through hidden layers to output. In iterative networks, data flows both ways, and previous output affects current input. Fully connected networks have every node linked to all others [16] - [18] (See Figure 6).

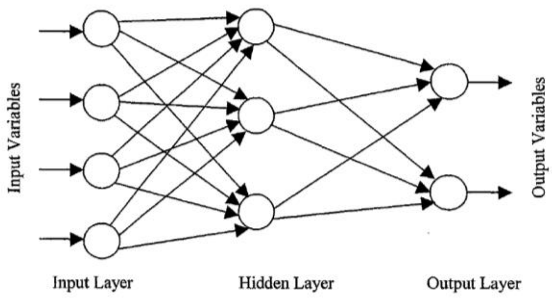

Figure 6. The Schematic representation of a three-layer neural netwok

2.5.1 Neuron Input Calculation

Each neuron in a neural network receives inputs from the previous layer or the input data itself. The inputs are weighted, and then summed up with a bias term. The formula for calculating the input to a neuron as shown in Formula 1.

$$Z = \sum_{i=1}^{n}(wi * xi) + B \tag{1}$$

z is the total input to the neuron, n is the number of inputs, wi is the weight associated with the ith input, xi is the iith input value, and B is the bias term.

2.5.2 Activation Function

Once the input to a neuron is calculated, an activation function is applied to introduce non-linearity and determine the neuron's output. The activation function is typically denoted as ff and can vary depending on the network's requirements. Common activation functions include sigmoid, tanh, ReLU, and softmax as shown in Formula 2.

$$a = f(z)a = f(z) \tag{2}$$

a is the output of the neuron.

2.5.3 Feedforward Propagation

The output of each neuron in one layer serves as the input to the neurons in the next layer. This process is known as feedforward propagation. It continues until reaching the output layer. The formulas for feedforward propagation are shown in Formula 3 and 4:

$$x^{(1)} = W^{(1)} \cdot a^{(l-1)} + b^{(1)} \tag{3}$$

$$a^{(1)} = f(z^{(1)}) \tag{4}$$

l is the current layer, $W^{(1)}$ is the weight matrix associated with layer ll, $a^{(l-1)}$ is the output of layer $l-1$, and $B^{(1)}$ is the bias vector associated with layer ll.

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2.6 Model Evaluation

The evaluation of performance is a crucial step to assess the effectiveness of a proposed model and draw conclusions from the conducted study. One of the commonly used methods to measure the error of a predictive model is K-fold cross-validation. This method is similar to repeated random subsampling, but it ensures that there is no overlap between any two test sets. In K-fold cross-validation, the training data is divided into k subsets of equal size [19].

Table 2 presents a confusion matrix for binary classification that compares the distribution of the actual data and the predicted data generated by the model. There are four types of confusion matrices that can be used to calculate performance metrics such as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN).

Table 2. Confusion Matrix

Actual	Prediction Positive	Negative
Positive	(TP) True Positive	(FN) False Negative
Negative	(FP) False Positive	(TN) True Negative

Here is a simple explanation of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN):

True Positive (TP): This occurs when the model correctly predicts a positive outcome when the actual value is indeed positive. In simpler terms, it's a correct positive prediction.

False Positive (FP): This happens when the model incorrectly predicts a positive outcome when the actual value is negative. In other words, it's a false alarm for a positive result.

False Negative (FN): FN takes place when the model incorrectly predicts a negative outcome when the actual value is positive. It represents a missed positive prediction.

True Negative (TN): TN is when the model correctly predicts a negative outcome when the actual value is negative. It's a correct negative prediction.

These components are then used to calculate the classification performance metrics such as accuracy, precision, recall, and F1-Score [20]. Accuracy is the ratio of correct system predictions to the total number of prediction results. Formula 5 shows the formula for computing the accuracy value.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad (5)$$

Accuracy is usually estimated by using an independent test set that was not used at any time during the learning process. More complex accuracy estimation techniques, such as cross-validation and bootstrapping, are commonly used, especially with datasets containing a small number of instances[21].

3. Results and Discussions

3.1 Results

The dataset were further divided into training and testing data to assess the neural network model using the R Studio application as shown in Figure 7.

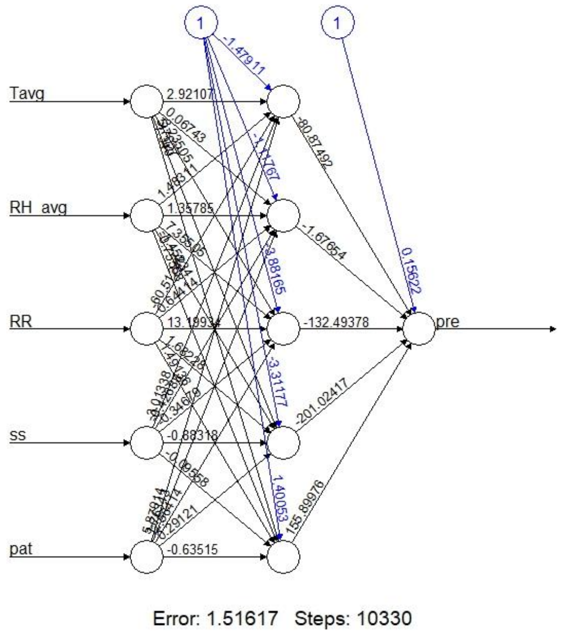

Figure 7. The implementation of neural network model using R Studio

The developed neural network (NN) model comprises of 5 input layers, 5 hidden layers, and 1 output layer, which predicts the planting time of Tobasco pepper. The model attained an error value of 1.516 and underwent 10330 steps during its development. Subsequently, the validation of the NN method was conducted by comparing the actual and predicted values using the R Studio application (See Figure 8).

```
> table(actual,prediction)
      prediction
actual   0   1
     0 146   0
     1  16  21
> sum(prediction==actual)/length(actual)
[1] 0.9125683
```

Figure 8 Confusion matrix of the prediction outcome validation

During the evaluation of the neural network model using 183 testing data, the following results were obtained: 146 True Positive (TP) values, 0 False Positive (FP) values, 16 False Negative (FN) values, and 21 True Negative (TN) values. The neural network model presented in the evaluation achieved a remarkable level of accuracy, with a reported value of 91.26%, based on the assessment of 183 testing data points. This high accuracy suggests its effectiveness in

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predicting chili planting time. In contrast, Rosdiana and Rismayana (2018) utilized the C45 decision tree algorithm to design an application for chili planting time prediction in West Java, attaining an accuracy of 72.2%. Subsequently, Walyadi (2019) expanded upon this work, enhancing the model by incorporating 16 predictive variables in the Magelang region, resulting in a predictive accuracy of up to 80%. While the neural network model surpasses both earlier models in accuracy, it is essential to consider other factors such as model complexity, data availability, and regional variations when evaluating their overall suitability for practical use. The novelty of this research lies in the integration of IoT technology and a sophisticated Neural Network model to predict the planting time of Bird's Eye Chili. The high accuracy achieved by the model, along with the consideration of various factors, positions it as a promising tool for practical use in agriculture.

3.2 Discussions

Exploring potential applications of the developed model beyond Tabasco pepper cultivation reveals exciting possibilities. The versatility of this model lies in its adaptability to other crop types or regions with similar environmental conditions.

The dataset's variables, including average temperature, humidity, rainfall, sunshine duration, and water use land, were meticulously adjusted to create suitable environmental conditions for chili plants. These variables can serve as a blueprint for adapting the model to different crops by tailoring the parameters to match their specific requirements. For regions sharing similar climate patterns, this model offers a valuable tool for optimizing planting schedules.

Scalability is a noteworthy feature of this model. As long as relevant data is available, it can be expanded to encompass various crops and geographic areas. This adaptability ensures that the model can support agricultural decision-making on a broader scale, helping farmers across diverse regions maximize crop yield.

Moreover, the model's versatility extends to addressing broader agricultural challenges, such as the impact of climate change on planting seasons. By fine-tuning the model with updated climate data and evolving crop preferences, it can assist in adapting farming practices to the changing environment.

In conclusion, the developed model's applications extend far beyond Tabasco pepper cultivation. Its scalability, adaptability, and versatility make it a powerful tool for optimizing planting decisions, whether for different crops or regions facing similar environmental conditions. This model holds the potential to enhance agricultural practices and contribute to sustainable crop production in various contexts.

4. Conclusion

This study conducted an experiment by developing a prototype IoT-based device that would be a parameter for Predicting the Planting Time of Bird's Eye Chili Based on Environmental Conditions using a machine learning algorithm model of artificial neural networks. The obtained accuracy value of 91.26% is indeed quite high, indicating a promising prediction model for Tabasco pepper planting time. Further development can be carried out by incorporating stream datasets that can be taken directly from sensors in the surrounding environment from where Tabasco peppers are planted. This approach involves using real-time data collected through sensors placed in the observation area to monitor the environmental conditions suitable for planting Tobasco pepper.

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