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Utilizing IoT-Enhanced Multilayer Perceptron and Run Length Encoding for Classifying Plant Suitability Based on pH and Soil Humidity Parameters

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Abstract

This research proposes an IoT-based system for classifying plant suitability using pH data and soil humidity parameters. The system utilizes Run-Length Encoding (RLE) to compress sensor data, which is transmitted to a database server via the Esp8266 module. A Multilayer Perceptron (MLP) algorithm is employed to classify the data, achieving an accuracy of 0.82 with only two parameters. The classification results are displayed on a website, providing real-time recommendations for farmers. The system's performance is evaluated using a dataset from Kaggle. The Kaggle dataset contains 2200 instances for 22 different plants and the results show that the proposed system can effectively classify plant suitability based on environmental factors. This research contributes to the development of IoT-based recommendation systems for precision agriculture, and future studies can build upon this work to improve accuracy and quality.

Keywords: Multi-layer Perceptron, Smart Agriculture, Internet of Thing, Run-length encoding

1. INTRODUCTION

The increasing demand for agricultural production in Indonesia has made soil fertility a crucial parameter in determining the quality of crops consumed and processed by the population. Farmers require specific data, particularly regarding soil pH and surrounding soil humidity levels, to achieve optimal harvests. This information is essential for determining which plant species are best suited to the local soil and climate conditions, ultimately leading to improved crop yields.

Despite the rising adoption of advanced technologies, particularly in artificial intelligence (AI) and the Internet of Things (IoT), within the agricultural sector, challenges persist. These technologies are designed to boost production, reduce waste and costs, and minimize environmental impact [1]. For instance, AI-driven IoT applications can optimize crop yields by monitoring soil pH and humidity levels, providing farmers with real-time data on these parameters and

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recommending suitable crops based on the measured conditions. However, farmers currently rely on laboratory soil testing to determine these crucial parameters. This method not only requires a trip to the laboratory but also can produce data that is not entirely accurate [2]. The need for precise, real-time data collection directly in the field remains a significant challenge for farmers. Overcoming this challenge necessitates replacing traditional data collection methods with IoT-based sensors [3].

Sensors, such as pH and humidity sensors integrated with Arduino microcontrollers and ESP-8266 modules for internet connectivity, offer a solution by allowing farmers to monitor soil conditions in real-time without physically measuring the plantation area. These sensors detect and respond to inputs from the physical environment, converting analog voltage values into digital readings [4]. The integration of IoT plays a crucial role in processing data collected from these sensors. Arduino's Input/Output capabilities facilitate various sensor inputs and corresponding outputs, accommodating multiple sensors whose data are stored on a database server. This server stores sensor data sent from Arduino via the ESP8266 module, enabling internet network integration and wireless data transfer for analysis [5].

Before sensor data is transferred to the database server, it is processed using the Run-length encoding (RLE) method within the Arduino. RLE is a data compression technique that ensures smooth data transmission and prevents data loss by preserving the sequence of data values, allowing for efficient transmission of repeated data [6]. After processing with RLE, the data is transmitted to the database server for storage and analysis using the Multi-layer Perceptron (MLP) algorithm. MLP, a neural network-based model, is favored for its ability to enhance model efficiency with each iteration [7]. The stored data is used for classification, determining optimal plant conditions based on the pH and soil humidity levels captured by the sensors. The results are then displayed on a website, providing farmers with real-time insights into soil conditions and enabling them to identify the most suitable crops for their specific soil conditions.

The utilization of IoT in agriculture is a rapidly expanding research field, evolving alongside the development of AI. The agricultural industry is undergoing a revolution driven by sensors, IoT, big data, and cloud technology [8]. To support IoT infrastructure in agriculture, several factors must be considered, including hardware devices, data analysis, maintenance, mobility, and infrastructure [9]. Research by [10] on developed a system to help farmers evaluate land for cultivation, categorizing it into four decision classes: highly suitable, suitable, moderately suitable, and unsuitable. This system relies on inputs from various sensors and decision-making using an MLP algorithm, with Raspberry Pi 3 for data collection and WEKA tools for data processing. Another study by [11] to

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used N, P, K, pH, temperature, soil moisture, and rainfall for crop recommendations, with MLP, JRip, and decision table classifiers achieving an accuracy of 98.2273% with a processing speed of 8.05 seconds.

This research aims to develop a system that integrates Arduino with the ESP 8266 for field data collection and utilizes Python programming to process the data using the MLP algorithm, thereby providing farmers with accurate, real-time information to improve crop selection and yield.

2. METHODS

2.1. Dataset

The data used in this research utilizes a public dataset from Kaggle as training data [12], which consists of N - the ratio of nitrogen content in the soil, P - the ratio of phosphorus content in the soil, K - the ratio of potassium content in the soil, temperature - in degrees Celsius, humidity - relative humidity in %, pH - the pH value of the soil, and rainfall - in mm, the provided data in the table contains recommended plants with numerical value ranges for the 7 different parameters. The Kaggle dataset contains 2200 instances for 22 different plants. This dataset covers various parameters that can be used for land suitability analysis and to create accurate land suitability classifications for specific plants. In this research, only pH and humidity data are used as references for suitable plant selection on a particular land, as they are compatible with the sensors used in the IoT device, as shown in the IoT framework design in Figure 1, which only uses two sensor inputs, namely pH and humidity sensors.

2.2. Data Preprocessing

Initially, the data had 7 parameters, but only 2 parameters were taken, namely pH data and soil humidity data, from the Kaggle dataset as shown in Table 2.

Table 2. Table crop recommendation with numeric data.

No	Parameter	Data Amount	Crop Recommended
1	2	100	rice
2	2	100	maize
3	2	100	chickpea
4	2	100	kidneybeans
5	2	100	pigeonpeas
6	2	100	mothbeans
7	2	100	mungbean
8	2	100	blackgram
9	2	100	lentil

No	Parameter	Data Amount	Crop Recommended
10	2	100	pomegranate
11	2	100	banana
12	2	100	mango
13	2	100	grapes
14	2	100	watermelon
15	2	100	muskmelon
16	2	100	apple
17	2	100	orange
18	2	100	papaya
19	2	100	coconut
20	2	100	cotton
21	2	100	jute
22	2	100	coffee
	Total	2000	

The selection of 2 parameters was done to match the sensor inputs used in the built IoT architecture. The data was then divided into 0.33 parts for training data, testing data, and prediction using the Python programming language. The trained data will later be synchronized with the existing database on the SQL server to enable real-time prediction of plant suitability on the land and display it on the website.

2.3. Research Methods

2.3.1 Run-Length Encoding (RLE)

Run-length encoding (RLE) is one of the oldest data compression algorithms, a method used to compress large data into smaller, more compact data. The data is compressed by identifying repeated characters in a single row and storing the count (called a run) and each character (called a run value) as the target data[13].

2.3.2 Multi-layer Perceptron (MLP)

Multi-Layer Perceptron (MLP) is a type of feed-forward neural network (FFNN) that has been widely used in various modeling fields. An MLP model consists of three layers (one input layer, one output layer, and one or more hidden layers) comprising several neurons, which are organized within these layers [7], [10]. The number of neurons in the input and output layers is chosen to be equal to the number of input and output variables of the network, respectively. However, the optimal number of neurons in the hidden layer is determined using a trial-and-error method to achieve optimal results, and the model structure is based on the lowest Root Mean Squared Error (RMSE) value [14]. For instance, the input

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receives n features as input (x = x1 + x2 + x3 + x4 + x5 ... xn). These n features are then passed to the input function u, which calculates the weighted sum for the input layer as shown in Equation 1.

$$U_{(x)} = \sum_{i=1}^{n} w_i x_i \quad (1)$$

The output will be forwarded to the activation function {f} of the sigmoid nodes from 0 to 35 [11].

2.4. Internet of Things

The Internet of Things (IoT) is a technology designed to connect all integrated objects into a network via the Internet, involving all types of computer technologies, including hardware such as microcontroller PCBs, sensors, and software that encompasses operating systems and artificial intelligence algorithms [2].The IoT system works by combining several interconnected interfaces, including sensors, microcontrollers, the Internet, database servers, and websites. The sensor sends a digital signal in the form of voltage to the Arduino's ADC port, which is then calibrated to produce pH and humidity values. The output from Arduino, consisting of pH and humidity values, is sent to the database server using the Internet and ESP8266 as a connector from Arduino to the database server, allowing real-time access to the website. The IoT framework can be seen in Figure 1.

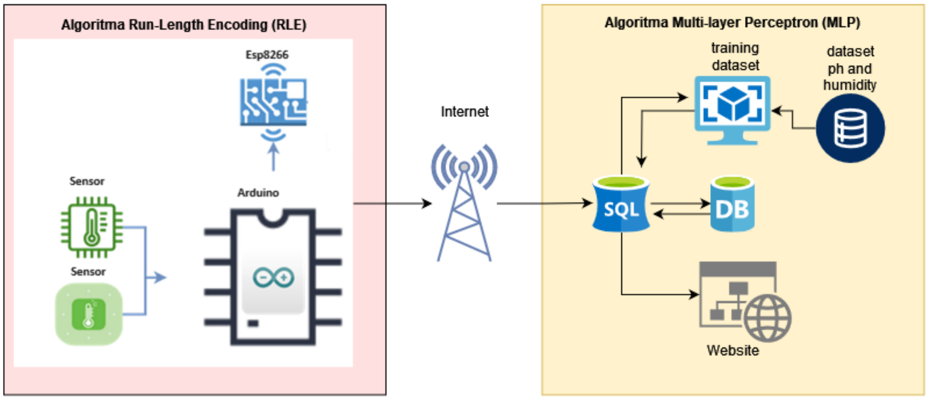

Figure 1. Framework Internet of Thing (IoT)

3. RESULTS AND DISCUSSION

In this section, the process of acquisition of sensor data, data compression using Run-Length Encoding (RLE) on Arduino before transmission, training, and testing of the dataset using Python, and prediction using Multilayer Perceptron

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(MLP) will be explained. Additionally, the classification result will be displayed on the website.

3.1 Run-Length Encoding (RLE)

The data acquisition process uses pH sensors and soil humidity sensors, which send digital signals in the form of voltage to the Arduino's ADC port for calibration, as shown in Figure 2. The calibrated sensor data is then compressed using the Run-Length Encoding (RLE) algorithm to identify and replace repetitive data sequences with shorter representations, enabling the transmission of a large amount of data in real-time. The compressed data is then sent to the database server via the Esp8266 module, which is connected to the internet."

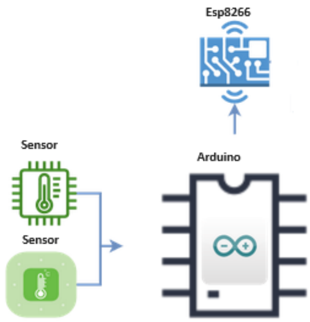

Figure 2. Sensor data is sent to Arduino for calibration

3.2 Multi-layer Perceptron

The formation of a neural network is created by an "input" layer, one or quite one "hidden" layer(s), and also the "output" layer. The final methodology of a particular three-layered neural network design is given in Fig 3[15]

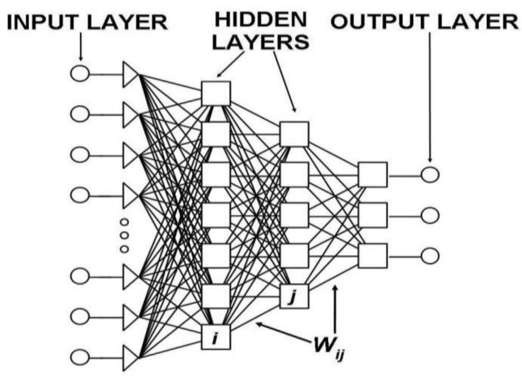

Figure 3. Conventional formation of Neural Network with 2- hidden layers

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With the schema in Figure 3, the input layer uses pH and moisture data collected directly from the plantation, while the output layer represents the type of plant suitable for the plantation area.

3.2.1 Training Dataset

Before performing classification, the data from the Kaggle dataset was taken with 2 parameters as shown in Table 3.

Table 3. Data set with 2 parameters

No	Humidity	Ph	Label
1	82.00274	6.502985	Rice
…	…	…	…
101	71.57477	6.931757	Maize
…	…	…	…
201	16.98861	7.485996	chickpea
…	…	…	…
301	20.59542	5.685972	kidneybeans
…	…	…	…
401	57.92887	6.031608	pigeonpeas
…	…	…	…
501	64.70931	3.692864	mothbeans
…	…	…	…
601	87.80508	7.185301	mungbean
…	…	…	…
701	63.19915	7.454532	blackgram
…	…	…	…
801	63.49802	7.60411	Lentil
…	…	…	…
901	91.63536	5.922936	pomegranate
…	…	…	…
1001	76.249	6.149934	Banana
…	…	…	…
1101	47.54885	5.954627	Mango
…	…	…	…
1201	81.54157	6.112306	Grapes
…	…	…	…
1301	80.92254	6.283818	watermelon
…	…	…	…
1401	94.11878	6.776533	muskmelon
…	…	…	…

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No	Humidity	Ph	Label
1501	90.69489	5.521467	Apple
…	…	…	…
1601	92.51078	6.354007	Orange
…	…	…	…
1701	91.49725	6.793245	Papaya
…	…	…	…
1801	92.86057	6.420019	coconut
…	…	…	…
1901	79.19732	7.231325	Cotton
…	…	…	…
2001	72.24851	6.002525	Jute
…	…	…	…
2101	57.3647	7.261314	Coffee
…	…	…	…

The data was then trained using a Python program with activation='sigmoid', optimizer="adam", and epochs=100000, resulting in an accuracy of 0.82 as shown in Figure 3.

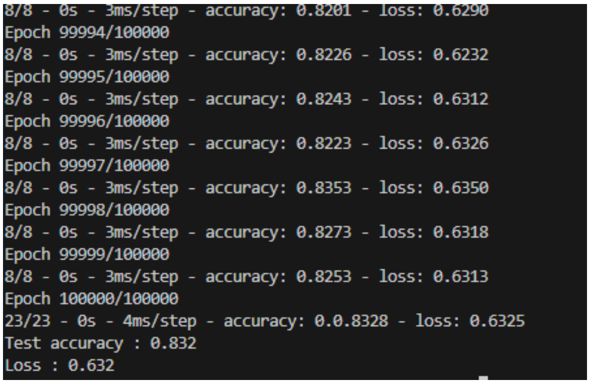

Figure 4. Training dataset result

The training data results will be saved as a reference for future data prediction. In research titled "IoT Framework for Measurement and Precision Agriculture: Predicting the Crop Using Machine Learning Algorithms", the accuracy performance percentage ranged from 98.2273% to 88.5909% for multilayer perceptron using 7 parameters [13]. In contrast, this study uses only 2 parameters, namely pH data and humidity data, as it adapts to the number of sensors used for real-time classification.

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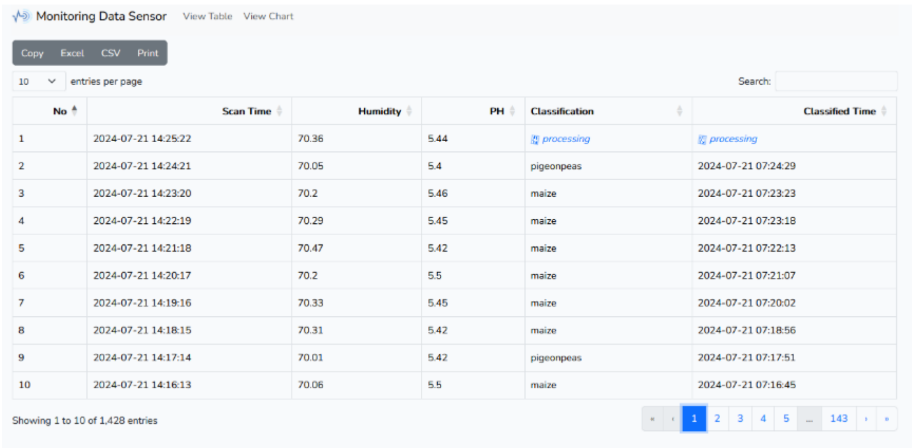
3.2.2 Classification Process

At this stage, a trial was conducted to collect pH and humidity data using Internet of Things (IoT) technology. The data was collected from a cornfield in the Indralaya area, and the data collection process can be seen in Figure 4.

Figure 5. pH and humidity data collection in the sugarcane field

The data collection was done in real time, and the data sent from Arduino to the database server will be displayed on the website, showing the data collection time, humidity value, pH value, and classification results. Unclassified data will be marked with a "processing" indicator, while classified data will display the classification results in the form of plant names, as shown in Figure 4.



Monitoring Data Sensor View Table View Chart

Copy Excel CSV Print

10 entries per page Search:

No	Scan Time	Humidity	PH	Classification	Classified Time
1	2024-07-21 14:25:22	70.36	5.44	processing	processing
2	2024-07-21 14:24:21	70.05	5.4	pigeonpeas	2024-07-21 07:24:29
3	2024-07-21 14:23:20	70.2	5.46	maize	2024-07-21 07:23:23
4	2024-07-21 14:22:19	70.29	5.45	maize	2024-07-21 07:23:18
5	2024-07-21 14:21:18	70.47	5.42	maize	2024-07-21 07:22:13
6	2024-07-21 14:20:17	70.2	5.5	maize	2024-07-21 07:21:07
7	2024-07-21 14:19:16	70.33	5.45	maize	2024-07-21 07:20:02
8	2024-07-21 14:18:15	70.31	5.42	maize	2024-07-21 07:18:56
9	2024-07-21 14:17:14	70.01	5.42	pigeonpeas	2024-07-21 07:17:51
10	2024-07-21 14:16:13	70.06	5.5	maize	2024-07-21 07:16:45

Showing 1 to 10 of 1,428 entries

1 2 3 4 5 … 143

Figure 6. Website display

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If the MLP server is active, a notification will appear when the classification is successful, and the MLP server will take a 5-second break before continuing the classification process. If there is no more data to be classified, the server will send a notification and take a 60-second break to reduce the website server load, as shown in Figure 5.

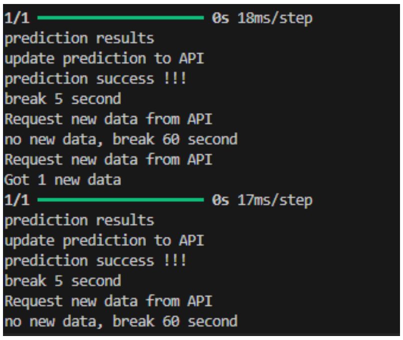

Figure 7: MLP Classification Process on the Server

3.2.3 Classification Performance

Validation is conducted using the multilayer perceptron algorithm. Testing will be performed with variations in learning rate, number of epochs, and hidden layers that will be applied during the testing with the system.

1) Multilayer Perceptron with 5 Hidden Layers

This experiment will implement the multilayer perceptron algorithm with an input structure consisting of 5 hidden layers, while the number of epochs used will be 10,000 epochs, 20,000 epochs, 50,000 epochs, 100,000 epochs, and 500,000 epochs. The data ratio for testing is 33.3%, training is 33.3%, and the test data for prediction is 33.3%, which divides the data into 3 groups. The results will include accuracy, precision, recall, F1-score, Cohen's kappa, MSE, and RMSE. These will be presented in Table 4.

Tabel 4. Results of MLP with 5 Hidden Layers

No	Epoch	Precision	Recall	F1-Score	Cohens kappa	MSE	RSME	Accuracy
1	10000	0.55	0.55	0.51	0.53	30.20	5.49	0.553
2	20000	0.56	0.56	0.52	0.54	20.99	4.3	0.57
3	50000	0.57	0.57	0.53	0.55	23.6	4.5	0.58
4	100000	0.63	0.62	0.62	0.62	23.99	4.7	0.68
5	500000	0.65	0.61	0.60	0.59	24.1	4.8	0.69

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The experiment that implemented 5 hidden layers using 10,000, 20,000, 50,000, 100,000, and 500,000 epochs has shown accuracy results.

2) Multilayer Perceptron with 10 Hidden Layers

This experiment applies a multilayer perceptron algorithm with an input structure consisting of 10 hidden layers. The number of epochs used in the experiment includes 10,000, 20,000, 50,000, 100,000, and 500,000 epochs. The data split ratio is 33.3% for testing, 33.3% for training, and 33.3% for prediction, dividing the data into three groups. The results for accuracy, precision, recall, F1-score, and accuracy are presented in Table 5.

Tabel 5 Results of MLP with 10 Hidden Layers

No	Epoch	Precision	Recall	F1-score	Cohens kappa	Mse	Rsme	Accuracy
1	10000	0.66	0.66	0.65	0.65	21.70	4.6	0.7004
2	20000	0.64	0.65	0.61	0.66	26.90	5.18	0.73
3	50000	0.64	0.65	0.612	0.63	26.90	5.18	0.7337
4	100000	0.67	0.63	0.62	0.62	27.77	5.21	0.7606
5	500000	0.68	0.59	0.57	0.57	28.43	5.3	0.7823

The experiment implementing 10 hidden layers and using 10,000, 20,000, 50,000, 100,000, and 500,000 epochs has demonstrated accuracy results.

3) Multilayer Perceptron with 15 Hidden Layers

This experiment applies a multilayer perceptron algorithm with an input structure consisting of 10 hidden layers. The number of epochs used in the experiment includes 10,000, 20,000, 50,000, 100,000, and 500,000 epochs. The data split ratio is 33.3% for testing, 33.3% for training, and 33.3% for prediction, dividing the data into three groups. The results for accuracy, precision, recall, F1-score, and accuracy are presented in Table 6.

Tabel 6. Results of MLP with 10 Hidden Layers

No	Epoch	Precision	Recall	F1-score	Cohens kappa	Mse	Rsme	Accuracy
1	10000	0.66	0.66	0.65	0.65	21.70	4.6	0.70
2	20000	0.66	0.67	0.66	0.66	20.99	4.3	0.712
3	50000	0.67	0.67	0.66	0.66	23.6	4.5	0.73
4	100000	0.68	0.67	0.66	0.66	24.94	4.99	0.76
5	500000	0.64	0.65	0.66	0.63	26.90	5.18	0.81

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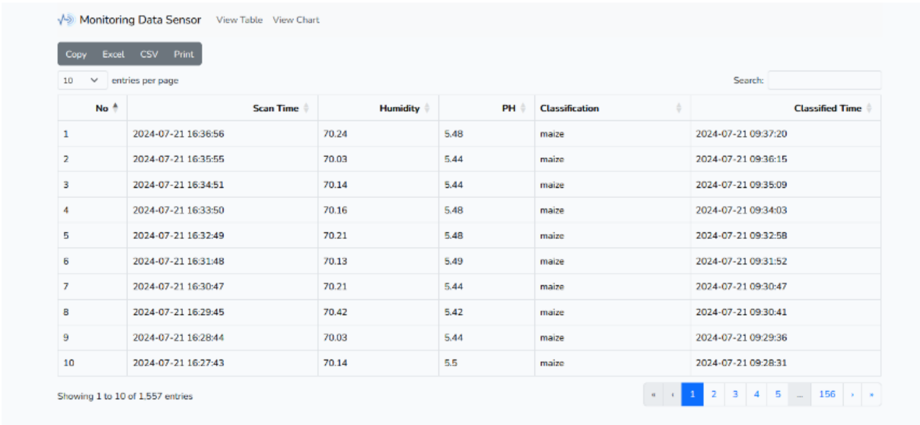
The experiment implementing 15 hidden layers and using 10,000, 20,000, 50,000, 100,000, and 500,000 epochs has demonstrated accuracy results.

Finally, after the data from Arduino is classified using the multi-layer perceptron algorithm in real-time, the results will be displayed on the website with indicators of humidity, pH, and classification results, as shown in Figure 8.



No	Scan Time	Humidity	PH	Classification	Classified Time
1	2024-07-21 16:36:56	70.24	5.48	maize	2024-07-21 09:37:20
2	2024-07-21 16:35:55	70.03	5.44	maize	2024-07-21 09:36:15
3	2024-07-21 16:34:51	70.14	5.44	maize	2024-07-21 09:35:09
4	2024-07-21 16:33:50	70.16	5.48	maize	2024-07-21 09:34:03
5	2024-07-21 16:32:49	70.21	5.48	maize	2024-07-21 09:32:58
6	2024-07-21 16:31:48	70.13	5.49	maize	2024-07-21 09:31:52
7	2024-07-21 16:30:47	70.21	5.44	maize	2024-07-21 09:30:47
8	2024-07-21 16:29:45	70.42	5.42	maize	2024-07-21 09:30:41
9	2024-07-21 16:28:44	70.03	5.44	maize	2024-07-21 09:29:36
10	2024-07-21 16:27:43	70.14	5.5	maize	2024-07-21 09:28:31

Figure 8: Website Display of MLP Classification Results

The humidity value ranges from 70 and the pH value is 50.4, which indicates that the maize plant is suitable for the soil condition. There are some differences in the classification results, as shown in Figure 4, which displays the classification results for pigeon peas with a pH range of 70 and humidity of 50.4, because the parameters used as classification references are only two, and the humidity and pH ranges for each plant are not too far apart, which has been trained with previous data.

3.3 Discussion

The results of this study demonstrate the effectiveness of using a combination of Run-Length Encoding (RLE) for data compression and the Multi-layer Perceptron (MLP) algorithm for real-time classification of agricultural data collected via IoT sensors. The methodology implemented here shows a clear path towards optimizing data transmission and enhancing the accuracy of crop suitability predictions.

The application of RLE on the sensor data before transmission significantly reduced the amount of data sent to the database server. This reduction is critical in real-time agricultural monitoring, where large datasets need to be processed and transmitted efficiently to avoid latency issues. By compressing repetitive data sequences into shorter representations, RLE enabled smoother and faster data

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transmission, which is essential for maintaining the integrity and speed of real-time data collection. The effective use of RLE in this context not only minimizes data transmission time but also reduces the potential for data loss, ensuring that the system provides accurate and timely information to the farmers.

The MLP algorithm's performance in classifying crop suitability based on pH and humidity data highlights its robustness in handling agricultural datasets, even with a limited number of input parameters. The MLP was trained using a dataset with only two parameters—pH and humidity—yet achieved an accuracy of 0.82 during training. This accuracy, while lower than other studies that utilized more parameters, is commendable given the constraints. It suggests that even with minimal input data, the MLP can effectively discern patterns and make predictions that align closely with more complex models.

The experiments conducted with varying numbers of hidden layers and epochs provided valuable insights into the model's behavior under different configurations. As the number of hidden layers and epochs increased, the accuracy of the model improved, reaching up to 0.81 with 15 hidden layers and 500,000 epochs. This progression underscores the importance of fine-tuning neural network parameters to achieve optimal performance. However, it is also evident that diminishing returns may occur as the number of layers and epochs increases, suggesting a need for balancing model complexity with computational efficiency.

The integration of the MLP classification results into a user-friendly website interface further demonstrates the practical applicability of the system. The website's ability to display real-time data, including humidity, pH, and crop suitability classifications, provides farmers with immediate insights, enabling them to make informed decisions about crop management. The inclusion of status indicators for unclassified and classified data enhances the transparency and usability of the system, ensuring that users are aware of the system's current processing status.

Despite the promising results, the study also highlights some challenges. The limited number of input parameters (only pH and humidity) led to classification overlaps, as seen in the similar classification results for maize and pigeon peas. This suggests that incorporating additional parameters, such as temperature, soil type, and nutrient levels, could improve the precision of the classifications. Furthermore, the study's reliance on a relatively small dataset for training may have constrained the model's generalizability. Future work should explore expanding the dataset and integrating more comprehensive environmental factors to enhance the system's predictive capabilities.

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This study successfully demonstrates the potential of combining IoT-based data collection, data compression via RLE, and neural network-based classification with MLP for improving agricultural decision-making processes. The system developed provides a reliable, real-time method for farmers to monitor soil conditions and select appropriate crops based on pH and humidity levels. However, further research is needed to refine the model by incorporating additional environmental parameters and expanding the training dataset to increase the accuracy and generalizability of the classification results.

4. CONCLUSION

The study leads to several important conclusions: The application of the MLP algorithm for classifying suitable crops based on soil pH and moisture levels is highly dependent on the quality and diversity of the training data as well as the selected input parameters. The RLE algorithm proved to be an effective data compression method, particularly in scenarios with large amounts of redundant data, significantly reducing data transmission times. The MLP algorithm achieved its best performance with higher epochs and an increased number of hidden layers; however, this also resulted in longer computation times, which were justified by the corresponding improvements in accuracy. Notably, the difference in accuracy between using 10 and 15 hidden layers was minimal, with an approximate margin of only 0.3%, suggesting that beyond a certain point, increasing model complexity yields diminishing returns in terms of accuracy.

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