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AI Assisted and IOT Based Fertilizer Mixing System

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ABSTRACT

Agriculture techniques, particularly fertilizer mixing, have significant impacts on crop productivity. Introducing IoT technology to agriculture can enhance productivity, and machine learning offers a mechanism to gain insights from data, making agricultural practices more efficient. This research aims to design an AI-assisted and IoT-based fertilizer mixing system for greenhouses. This system utilizes sensor data and AI algorithms, specifically the Support Vector Machine (SVM), to optimize fertilizer application. Results from the SVM classifier showed a 100% accuracy rate for temperature and humidity, 65% accuracy for phosphorus, 86% for nitrogen, and 100% for potassium. These findings demonstrate the potential of the proposed system to improve fertilizer efficiency while reducing labor and resource waste.

Keywords: IoT, SVM classifier, Fertilizer

1. INTRODUCTION

The agricultural sector remains pivotal to the economic development and sustenance of many nations, serving as a linchpin for progress and globalization. However, traditional agricultural practices grapple with multiple challenges, notably inconsistent yields, vulnerability to climate change, expansive land requirements, and escalating labor costs. Such constraints amplify the looming risks of food scarcity. A seminal component of agricultural optimization is the strategic application of fertilizers, notably the Nitrogen, Phosphorus, and Potassium (NPK) mix. Most soils inherently lack the macronutrients crucial for optimal plant growth, making fertilization indispensable. Yet, manual approaches to nutrient provision are often imprecise, leading to resource wastage and suboptimal yields. With the advent of Industry 4.0 technologies, including AI, IoT, and machine learning, a transformative shift is underway. These technologies, as highlighted by Krstevska et al. [1] and Ramli et al. [2augment productivity and usher in tailored solutions that could revolutionize fertilizer application and overall agricultural efficiency. Addressing these challenges, this project seeks to harness the capabilities of AI and IoT, deploying a cost-effective fertilizer mixing system, fine-tuned by machine learning, to enhance nutrient provision and foster sustainable farming practices.

2. LITERATURE REVIEW

A series of innovative approaches to revolutionize traditional agricultural practices have emerged in recent years. Ramli et al. [2] introduced an automated nutrient solution mixing system that

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leverages electrical conductivity (EC) to ensure precise fertigation for hydroponics. The solution is designed to automatically match the required EC level, effectively addressing the issues inherent in manual mixing. Elhassan Mohammed Elhassan Ahmed et al. [3] delved into the realm of farm automation using IoT. They proposed a system integrating soil moisture and climate sensors to monitor and regulate aspects such as irrigation, temperature, and humidity, ensuring optimal crop growth conditions. Garg et al. [4] emphasized the integration of IoT and machine learning for precision agriculture. Their multimodal approach employed state-of-the-art models for crop disease detection and damage prediction, advocating for comprehensive solutions incorporating image classification and machine learning techniques. Further exploring the combination of IoT and AI, Kanuru et al. [5] introduced an intelligent farming technique that employed machine learning algorithms to optimize pesticide and fertilizer applications based on sensor data. With similar intentions, Nyakuri et al. [6] highlighted a deep learning model designed for edge devices, focusing on intelligent irrigation and fertigation with remarkable accuracy. Meanwhile, Ragavi et al. [7] embarked on integrating agrobot systems with IoT and AI, offering an amalgamation of seed sowing, continuous monitoring, and data-driven agricultural insights. Lastly, Bhuvaneswari Swaminathan et al. [8] put forth a comprehensive system that combines multiple sensors with deep learning algorithms to provide tailored fertilizer recommendations to farmers, aiming for efficient fertilizer use and improved yields.

Contrasting the research, our work uniquely combines AI-assisted IoT-based fertilizer mixing systems with machine learning methodologies tailored for specific nutrient provision to plants. Rather than focusing solely on fertigation or automation, we have amalgamated these domains to create a seamless, cost-effective, and efficient system. The fusion of these technologies aims to optimize resource utilization, reduce wastage, and ultimately amplify agricultural yields. This synthesis of machine learning, AI, and IoT, while taking cues from existing research, offers a fresh perspective and solution to the complexities of modern-day agriculture.

3. METHODOLOGY

The methodology employed in this research is bifurcated into two primary segments: the integration and functioning of the IoT hardware and the development and deployment of the Machine Learning model. These components work synergistically to ensure efficient data collection, analysis, and dissemination of information through a user-friendly web interface. Figure 1 shows the overall block diagram of the system. Figure 1 shows the overall block diagram of the system.

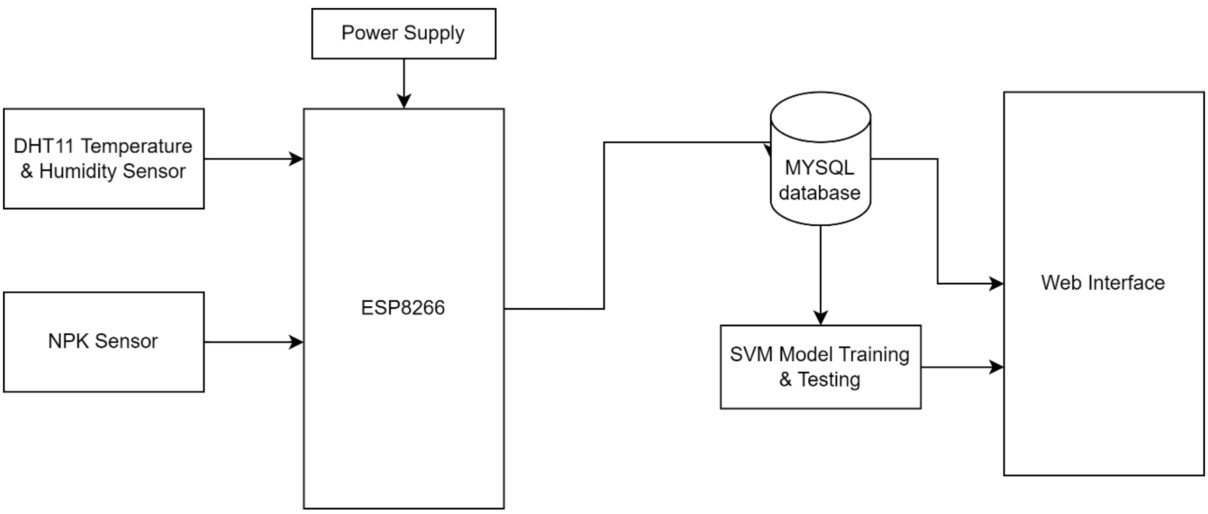


Figure 1: Block diagram of the system.

3.1 IoT Hardware Integration and Data Collection

This research employs a comprehensive IoT-based approach to collect and transmit critical agricultural data. At the heart of this system is the ESP8266 module. Programmed using the Arduino IDE, this module connects wirelessly to the internet via its built-in Wi-Fi capabilities.

The NPK sensor, a crucial component, is interfaced with the ESP8266 module. This sensor offers real-time monitoring of essential soil nutrients, namely nitrogen, phosphorus, and potassium. By doing so, it provides insights crucial for understanding plant growth and health dynamics.

Parallelly, the DHT11 sensor is integrated into the system, which is responsible for gauging temperature and humidity. This sensor continuously records environmental conditions, presenting data indispensable for accurate plant health assessments. Connected to a microcontroller, the DHT11 ensures regular retrieval and transmission of these environmental parameters.

Data from both sensors is systematically collected by the ESP8266 module and transmitted via HTTP POST requests to an Apache-hosted web server. Once this data is successfully uploaded, it's stored in a MySQL database, setting the stage for subsequent analysis and machine learning applications.

3.2 Machine Learning Model

Our methodology was rooted in the comprehensive data collection phase that spanned two weeks. During this time, sensors diligently recorded data hourly, capturing intricate details that would serve as the foundation for our predictive model. With its high granularity, this rich dataset was stored in a MySQL database, from where it was fetched for further analysis.

After extracting the data, the initial challenge was handling missing values and ensuring the dataset's integrity. We addressed gaps either by statistically imputing these values or, if deemed necessary, removing the affected entries. Following this, the numerical data underwent scaling and normalization processes to ensure equal treatment of every feature during the predictive phase. To amplify the depth of our dataset, we embarked on feature engineering. This process, aimed at capturing hidden patterns and relationships, enriched our data further, setting the stage for a robust predictive model.

Given the classification nature of our objective—distinguishing parameters like NPK ratios, temperature, and humidity into 'Normal' and 'Not Normal' categories—we turned to the Support Vector Machine (SVM) classifier. SVM was chosen due to its proven track record in handling linear and non-linear data while providing reliable predictions.

Training the SVM was meticulous. Its hyperplanes were calibrated to categorize our parameters adeptly. To ensure the model's consistent performance, a cross-validation approach was adopted. By splitting our dataset into multiple subsets and cycling through various train-test combinations, we could gauge the SVM's reliability and fine-tune its parameters.

Post-training, the SVM predictions were integrated into our web system dashboard. This dashboard showcased the results from the SVM classifier and proffered actionable recommendations. Whenever a parameter, temperature, humidity, or NPK ratio veered away from its optimal range, the system immediately suggested corrective measures.

In essence, our comprehensive methodology, from meticulous data collection to a user-centric dashboard, was designed to ensure timely and accurate insights for optimal plant nutrition, paving the way for enhanced agricultural productivity.

4. RESULTS AND DISCUSSION

Our system was implemented at UniMAP Green House in Padang Besar, Perlis, Malaysia. The system was tested for a month at the farm. Figure 2 below shows the system setup at the greenhouse.

Figure 2: System setup at UniMAP Green House.

The collected data is stored in the database and can be accessed on our web system. The web system displays the latest DHT11 and NPK sensor data. Figure 3 below shows the example web page from our system.

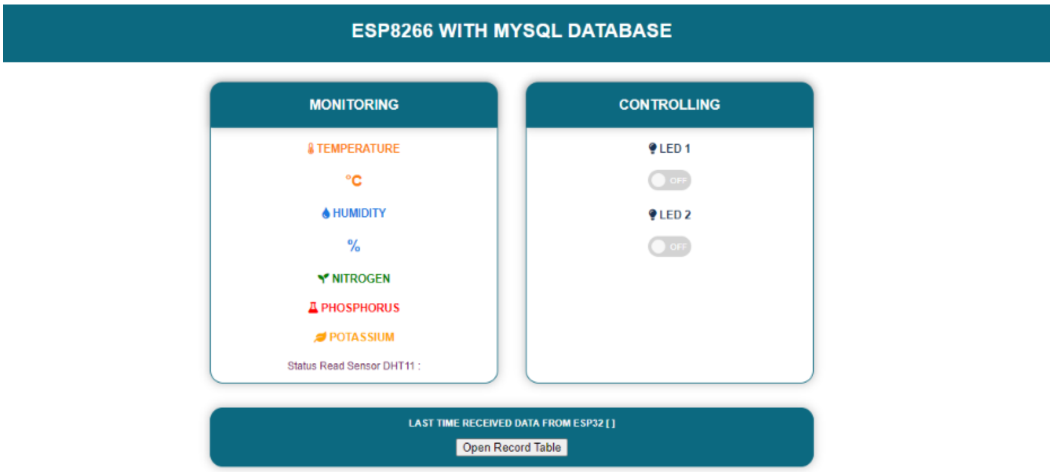
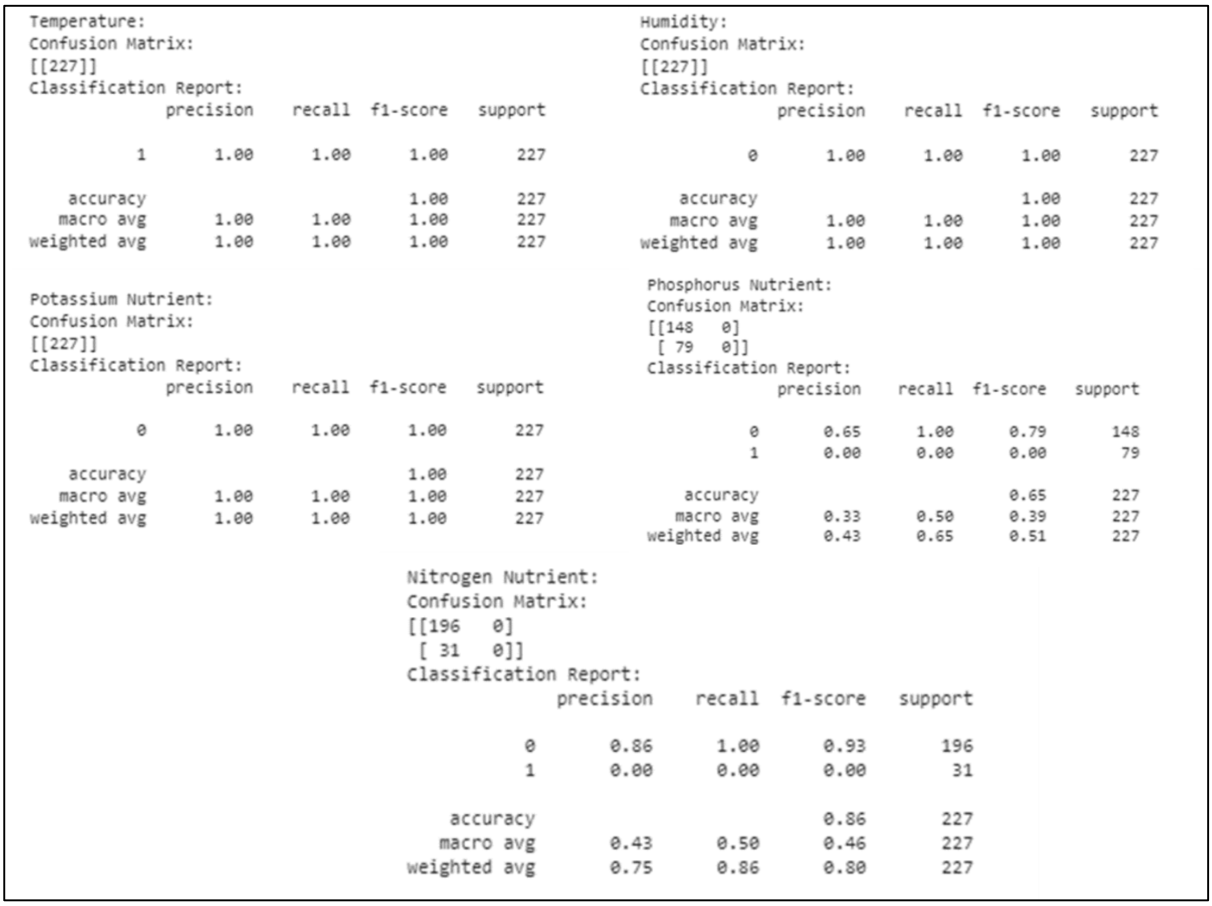


Figure 3: Main web page from the web system.

4.1 Model Evaluation

Utilizing the Support Vector Machines (SVM) for predictions, we conducted a thorough evaluation based on the collected dataset. Our results varied across parameters: The model performance on temperature, humidity and potassium displayed an impeccable 100% accuracy, evidenced by the precision, recall, and F1-score metrics all resting at 1.00. Conversely, the phosphorus and nitrogen, standing at 65% accuracy and 86%, revealed challenges, with a significant number of misclassifications. In particular, these models struggled to predict instances of nutrient deficiency, underscoring areas for potential refinement in our machine learning system. Figure 4 below shows the model performance for each data.



```
Temperature:
Confusion Matrix:
[[227]]
Classification Report:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00       227

    accuracy                           1.00       227
   macro avg       1.00      1.00      1.00       227
weighted avg       1.00      1.00      1.00       227

Humidity:
Confusion Matrix:
[[227]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       227

    accuracy                           1.00       227
   macro avg       1.00      1.00      1.00       227
weighted avg       1.00      1.00      1.00       227

Potassium Nutrient:
Confusion Matrix:
[[227]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       227

    accuracy                           1.00       227
   macro avg       1.00      1.00      1.00       227
weighted avg       1.00      1.00      1.00       227

Phosphorus Nutrient:
Confusion Matrix:
[[148   0]
 [ 79   0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.65      1.00      0.79       148
           1       0.00      0.00      0.00        79

    accuracy                           0.65       227
   macro avg       0.33      0.50      0.39       227
weighted avg       0.43      0.65      0.51       227

Nitrogen Nutrient:
Confusion Matrix:
[[196   0]
 [ 31   0]]
Classification Report:
              precision    recall  f1-score   support

           0       0.86      1.00      0.93       196
           1       0.00      0.00      0.00        31

    accuracy                           0.86       227
   macro avg       0.43      0.50      0.46       227
weighted avg       0.75      0.86      0.80       227
```

Figure 4: SVM model performance.

4.1.1 Temperature Prediction Results

Table 1 showcases the results of sensor data after SVM model prediction. The temperatures are classified based on a threshold, where a reading between 31 to 35 degrees is classified as "Normal". Any deviation from this range prompts a recommended action. For instance, a sample showing a temperature below this range suggests an increase in temperature, while those above are advised to decrease to bring it within the normal range.

Table 1: Temperature Prediction Results.

Temperature(°C)	Status	Recommended Action
32	Normal	No action required
28	Not Normal	Turn on heater
40	Not Normal	Turn on Fan
35	Normal	No action required

4.1.2 Humidity Prediction Results

The humidity data post-processing results are depicted in Table 2. Humidity levels between 70 and 100% are deemed "Normal". Readings outside this range are labeled "Not Normal", with accompanying recommendations to adjust the humidity. Humidity levels that are over 100% are classified as abnormal while giving the error action, indicating an error in sensor reading.

Table 2: Humidity Prediction Results.

Humidity(%)	Status	Recommended Action
70	Normal	No action required
65	Not Normal	Irrigation needed
90	Normal	No action required
1000	Not Normal	Error

4.1.3 Nitrogen Prediction Results

For nitrogen (Table 3), the "Normal" range is set between 50-200 mg/l. Readings falling below 50 mg/l are flagged as deficient, and the system advises necessary adjustments to increase nitrogen levels. Readings exceeding 200 mg/l indicate an excess, and recommendations are made to curtail the nitrogen concentration.

Table 3: Nitrogen Prediction Results.

Nitrogen(mg/l)	Status	Recommended Action
125	Normal	No action required
40	Not Normal	Nitrogen deficient, increase nitrogen concentration
250	Not Normal	Nitrogen excess, decrease nitrogen concentration
200	Normal	No action required

4.1.4 Potassium Prediction Results

The SVM model predictions results of potassium sensor analysis (Table 4) indicate that readings within the 120-250 mg/l range are classified as "Normal" for potassium. Readings below 120 mg/l indicate a deficiency and require a system recommendation to elevate potassium levels. Similarly, a reading above 250 mg/l indicates an excess and would prompt a recommendation to reduce potassium concentrations.

Table 4: Humidity Prediction Results.

Potassium(mg/l)	Status	Recommended Action
80	Not Normal	Potassium deficient, increase potassium concentration
175	Normal	Irrigation needed
250	Normal	No action required
300	Not Normal	Potassium excess, decrease potassium concentration

4.1.5 Phosphorus Prediction Results

For phosphorus (Table 5), readings between 20-50 mg/l are deemed "Normal". Results falling below 20 mg/l would be considered deficient, and the system would suggest steps to augment phosphorus concentrations. Conversely, readings above 50 mg/l indicate an excess, and corresponding recommendations will be provided to lower the phosphorus levels.

Table 5: Humidity Prediction Results.

Phosphorus(mg/l)	Status	Recommended Action
34	Normal	No action required
50	Normal	Irrigation needed
80	Not Normal	Phosphorus excess, decrease phosphorus concentration
10	Not Normal	Phosphorus deficient, increase phosphorus concentration

5. CONCLUSION

Our AI and IoT-driven fertilizer mixing system, utilizing the Support Vector Machine (SVM) algorithm, has displayed varying levels of accuracy across its parameters. With a commendable 100% accuracy in predicting temperature, humidity, and potassium levels, it underscores the system's proficiency in harnessing real-time data from NPK fluid and DHT11 sensors. However, the model faced challenges with phosphorus and nitrogen predictions, achieving 65% and 86% accuracy, respectively. Despite these impressive results, the system's efficacy remains contingent on sensors' reliability, training data quality, and consistent internet connectivity, emphasizing the need for careful calibration tailored to diverse agricultural needs. Future improvements are evident: incorporating a broader range of sensors, refining the SVM model with diverse datasets, engaging with agricultural experts, and integrating real-time weather data will enhance its precision and adaptability. As the system evolves, the potential of this AI and IoT combination to redefine global farming practices is palpable and promising.

ACKNOWLEDGEMENTS

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