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Advancing Agriculture 6.0: A Novel Residual Recurrent Unit for Crop Recommendation Using IoT Data

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ABSTRACT

In the era of smart technologies, Agriculture 6.0 utilized the most advanced technologies like artificial intelligence to enhance smart farming systems. It processed an optimal crop selection to maximize agricultural productivity based on specific environmental and soil conditions.

In this work, the new Deep Learning (DL) method is presented such as the Residual Recurrent Unit (RRU) Model which has two key modules Adaptive Scaling in the Transform Module and a Residual Connection Module. These modules optimized the model's sensitivity to varying inputs and also allowed untransformed data to directly influence the cell state to improve gradient flow. These features enhance the model performance by similar past and present inputs effectively. To further optimize performance, Siberian Tiger Optimization (STO) was used to tune the hyperparameter and attain the best possible result. The experimental result of the novel RRU model validated for both with and without STO based on various metrics like Accuracy, Precision, Recall, F1-Score, ROC, Loss, Cohen's Kappa and Matthews Correlation Coefficient etc. based on the validation, the proposed RRU model has achieved a superior performance in all aspects than traditional methods.

Also, this work included a hardware setup and collected data from a real field to investigate the model's performances based on soil and environmental factors. Therefore, real data results based on the novel RRU model provided an accurate crop recommendation and it is majorly supportive of precision agriculture with effectiveness in future.

Keywords: Agriculture 6.0, IoT data collection, novel RRU Model, hyperparameter tuning, accuracy, prototype performance.

INTRODUCTION

The rapid population growth is increased globally which is projected to reach 9.8 billion by 2050. The need agricultural advancements are also necessary to feed the whole living being. The new era in farming is Agriculture 6.0 which is integrated with a DL, the Internet of Things (IoT) and other advanced technologies (Neves et al., 2023). These integrations are used to enable ultra-precise farming Unlike traditional methodologies, Agriculture 6.0 provides a synchronized and responsive to monitor and optimizes continuously based on crop health, soil conditions and environmental factors given in Figure 1. These factors are associated with real-time IoT data taken from sensors in real fields (Neves et al., 2023). With this enhancement, a data-driven system is used to analyse local and global data streams using DL methods. It provided accurate decision-making of soil conditions, pest conditions, crop health and production, future climate conditions and sustainability “smart ecosystems” on farms (Patil et al., 2024).

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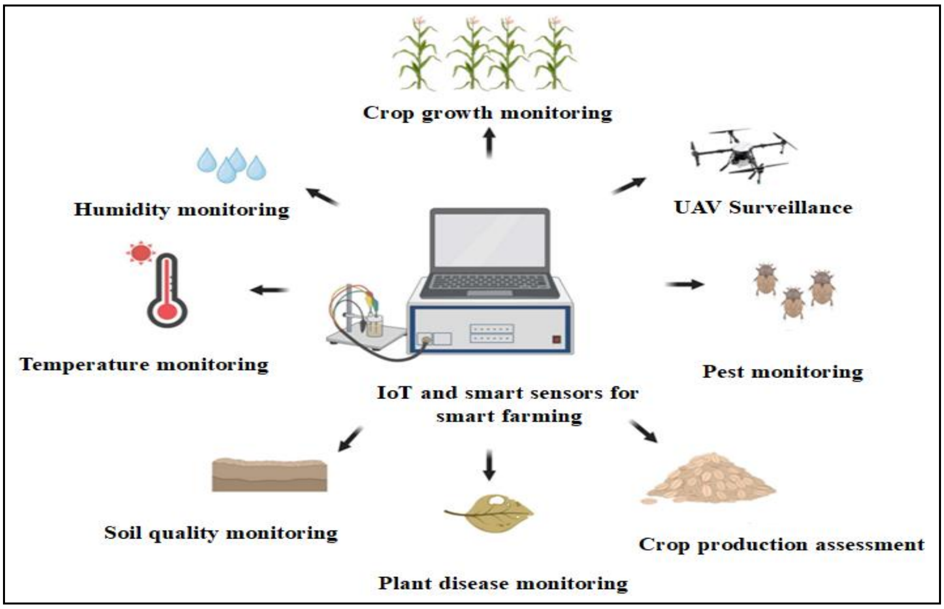

Figure 1. Advanced Farming Agriculture 6.0

The IoT integration handled real-time sensors like soil pH, N (Nitrogen), P (Phosphorus), and K (Potassium) nutrient levels, temperature, humidity and so on continually monitored by Medela et al. (2013). It assisted the farmers in monitoring crop health and growth precisely by Kaloxylos et al. (2013). It also assists farm workers in assessing pest attacks and plant diseases in real-time. The Loamy and sandy soil data provide a suitable for autonomous smart farming by Abba et al. (2019). Some sensors measured the residual nitrate level, organic matter soil concentrations and real-time transpiration rate by an author De Benedetto et al. (2019). Also, IoT supported the necessity of pesticide time and quantity in the field where excessive pesticides can contaminate the crops (Dutta et al., 2019; Rajak et al., 2023).

Advanced DL methods play a crucial role in a Data-Driven field that can handle surveillance, monitoring, controlling and decision-making effectively. Deep neural networks are mainly used for pattern recognition that consists of hidden layers to identify an object (Shrestha and Mahmood, 2019). Also, Zhuang et al. (2022) presented the DL method of AlexNet and VGGNet for a broadleaf weed dataset with a small image resolution. The ResNet-50-v1 method is done in a well-illuminated environment for weed classification by Leminen Madsen et al. (2020). In some cases, Trong et al. (2020) implemented a multi-model Deep Neural Network of late fusion used for Plant Seedlings and weeds data set with higher accuracy. In an advanced, hybrid method of Convolutional Neural Network (CNN) and You Only Look Once (YOLO) classification using various Grass, Creeping Thistle, Bindweed, and California poppy datasets for prediction (Saqib et al., 2023).

In Agriculture 6.0, crop recommendations are an important factor that supports soil and crop quality, productivity and prevention form diseases. For an accurate recommendation of crops, factors like historical yield, weather range, market demand and soil patterns are necessary. Kamatchi and Parvathi (2019) developed Neural Network to determine the best crops for specific weather conditions to improve the success rate of recommendations. To provide a farmer with transparent and accurate recommendations, the eXplainable AI (XAI) method is used by Shams et al. (2024). Also, Dey et al. (2024b) employed the edge devices to compare with six DL methods for crop recommendation. Recently, Xu et al. (2024), presented cascaded multi-task crop recommendations using the Shared-MMoE model and also gating network is optimized in every task. Popular models like

Support Vector Machine (SVM), XGBoost, Random Forest, KNN and Decision Tree are utilized for crop recommendations based on NPK, soil pH, and climatic factors by Dey et al. (2024a). The statistical methods used to define crop behaviour recommendation systems to attain highly advanced smart farming (Fassa et al., 2022).

In this work, the novel RRU architecture is proposed for an efficient crop recommendation. It has two advanced modules:

1) adaptive scaling-based transformer module to minimise oversaturation risks when handling real-time sensor data;

2) Residual Connection Module to improve gradient flow and enable long-term dependencies.

Also, Siberian Tiger Optimization (STO) tuned the RRU's hyperparameter to attain optimal performance in Agriculture 6.0. This proposed RRU model is applied for IoT data with a hardware prototype and analyses the data to provide an accurate crop recommendation based on their soil behaviours.

MATERIAL AND METHODS

Figure 2 shows the proposed workflow which has processed several steps for crop recommendation such as data collection, Pre-processing, Novel RRU classification with STO tuning and performance metrics evaluation.

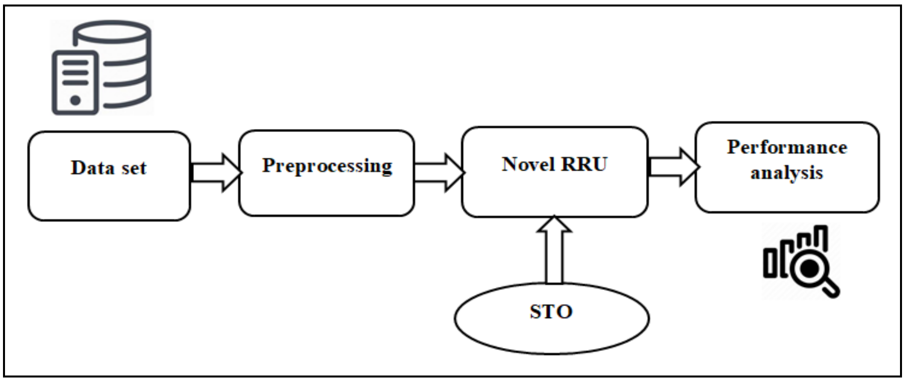

Figure 2. Proposed workflow

Dataset

In this work, the dataset is collected from real land using a sensor associated with IoT. This dataset includes soil and environmental parameters to analyse soil characters. The parameter includes N, P, and K which indicate the soil nutrient level for leaf development, root and seed production, water regulation and plant health. The dataset also collected rainfall that influences the environment and pH of the soil ranging from acidic to neutral. These factors may affect nutrient availability and suitability for different crops. This dataset can support applications like crop suitability analysis, precision agriculture and optimizing crop yield under specific conditions. After the data collection, the preprocessing is performed that handles data cleaning, normalization and splitting into training and testing sets to ensure data quality and consistency.

Proposed Method

In this work, the novel RRU method is proposed that is optimised by using an STO model to enhance the classification quality. The RRU model is an enhancement method of the Recurrent Neural Network (RNN) (Selvanarayanan et al., 2024) where adaptive scaling and residual connections are additionally included.

Novel RRU Model

The proposed RRU model is designed to improve the RNN's sensitivity by preventing oversaturation in the cell state. Figure 3 presents the RRU model's architecture that contains the main features of Forget Gate, Cell state update, output module, Adaptive Transform Module and Residual Connection Module, respectively.

Forget Gate: The forget gate (ft) is used to control and retain the data from the previous cell state Ct−1. The ft is multiplied by Ct−1 which retains past information in the current state. It is scaled to balance the past memory influences with new input.

Cell State Update: The cell state (Ct) is updated by combining Transform Module tr=tanh(it) and the scaled previous cell state Ct−1×ft that is expressed in the following.

$$Ct = tr + Ct - 1 \times ft \quad (1)$$

Thus, memory retention is controlled by this update by allowing an input to adapt and prevent the risk of oversaturation.

Adaptive Transform Module: Generally, Transform Module (tr) is represented as tanh(it), where it is the input at the current time step t. By applying the hyperbolic tangent (tanh) function, it restricted the value range for the cell state update that constrains values to a bounded range. This module prevented the cell state from larger size which led to oversaturation and reduced classification sensitivity. Here, the Transform Module is upgraded with a learnable scaling parameter (α) that is expressed in Equation (2).

$$tr = \alpha \cdot tanh(it) \quad (2)$$

This parameter (α) allows the Transform Module to adjust the degree of transformation to handle various signal intensities. This learning parameter scales the influence of the input dynamically to attain better control over the cell state and also prevent oversaturation.

Residual Connection Module: This module enables the model to retain previous input state information. That is where input ht−1 is added directly to the cell state update bypassing the transformation when needed even for a complex transformation. Therefore, the cell state update equation is given in the following.

$$Ct = tr + Ct - 1 \times ft + ht - 1 \quad (3)$$

Here, ht−1 indicates a residual connection that directly connected with Ct.

This feature was used to retain previous states' information and achieved an anti-oversaturation mechanism. The residual connection allows the gradient flow and mitigates the vanishing gradient issues by preserving significant information across time steps.

Output: Finally, RRU's output is evaluated at each time step that retains the modified cell state Ct benefits based on adaptive Transform and the residual connection. The output of RRU is expressed as:

$$ht = tanh(Ct) \quad (4)$$

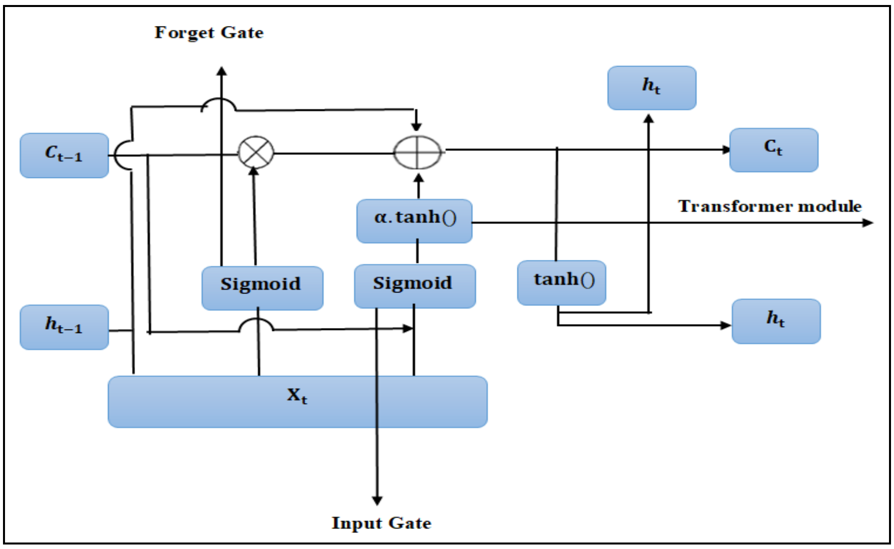

Figure 3. Novel RRU Architecture

From the result of RRU, both the adaptive Transform Module and the residual connection are used. The dynamic control of the input transformation is achieved by an adaptive scaling (α). It provides RRU as more versatile across various magnitudes and patterns. The residual connection retains previous states' data and enhances the stability and performances even in multi-class classification. Therefore, the novel RRU model provided a more robust to capture a temporal dependency with a classification sensitivity and also avoid an oversaturation.

RRU Parameter Tuning

Metaheiristics algorithms are used to solve real-world problems (Kavitha et al., 2024). To attain optimal accuracy in RRU's performances, the hyperparameter of RRU is tuned by using an **STO** method (Trojovský et al., 2022).

The STO method is based on the hunting behaviours of Siberian tigers that hunt prey and fight with brown bears. This algorithm is derived using these behaviours iteratively to identify an optimal solution for complex issues. The mathematical presentation of the STO Algorithm is presented below.

Initialization

- Initialize the tiger's position in the search space is generated randomly as **Population Matrix (X)**;
- The initial best solution **(Xbest)** is based on the objective function.

Phase 1: Prey Hunting

This phase presented an exploration that is the prey-searching behavior of tigers. When the Tigers are aimed to move closer to the prey that is represented by a better objective function value. The Position Update is expressed using the equation (5).

$$x_{i,j}^{P1s1} = x_{i,j} + rand\left(M_{i,j} - I_{i,j}x_{i,j}\right) \qquad (5)$$

where rand indicates a random number in [0, 1], Mi,j denotes a member of the population, Ii,j represents a random number from the set {1, 2} and j indicates The dimension index.

The Final Position Update is expressed by using equation (6)

$$x_{i,j}^{P1s2} = x_{i,j} + \frac{rand(ul_j - ll_j)}{t} \qquad (6)$$

where ulj, llj denotes the Upper and lower bounds of the function and t denotes the Current iteration number.

Phase 2: Fighting with a Bear

This phase mimics tigers fighting with a bear. The tigers select a bear's position and adjust their own position based on the bear's location, resulting in significant position updates.

Position Update (Stage 1):

$$x_{i,j}^{P2s1} = \begin{cases} x_{i,j} + rand\left(x_{k,j} - Ix_{i,j}\right), (F_k < F_i \\ x_{i,j} + rand\left(x_{i,j} - x_{k,j}\right), ELSE \end{cases} \qquad (7)$$

where Fk,Fi present objective function values of solutions xk and xi, respectively and rand indicates A random number in [0, 1].

Final Position Update (Stage 2):

$$x_{i,j}^{P2s2} = x_{i,j} + \frac{rand(ul_j - ll_j)}{t} \qquad (8)$$

Iterative Process

The STO algorithm alternates between the Prey Hunting and Bear Fighting phases, updating tiger positions and recalculating objective function values at each iteration. As better solutions are discovered, the best solution (Xbest) is updated accordingly.

Pseudocode for Optimizing RRU

1. **Initialize**:
   - Randomly initialize the population of candidate solutions representing RRU hyperparameters.
2. **Evaluate**:
   - Train the RRU model using the current candidate solutions;
   - Evaluate the trained model on the validation dataset;
   - Compute the validation accuracy as the objective value to maximize.
3. **Prey Hunting**:
   - Select a prey position based on fitness scores;

- Update tiger positions using the prey hunting equation (5).

4. **Bear Fighting**:
   - Select a bear position for each tiger;
   - Update tiger positions using the bear fighting equation (7).
5. **Iterate**:
   - Repeat steps 3 and 4 until the stopping criteria are met (e.g., maximum iterations or convergence).
6. **Output**:
   - Return the best solution (Xbest) and its associated accuracy.

The STO algorithm's novel approach to mimicking tiger behaviors ensures an effective search through the solution space. By combining exploratory (hunting) and exploitative (fighting) strategies, the STO method fine-tunes RRU hyperparameters to achieve higher classification accuracy and robustness.

Experimental result

The dataset was split into 70% for training and 30% for testing to ensure the model learns effectively while retaining enough data for evaluation. The training dataset (70%) was used to train the machine learning model by identifying patterns and relationships between the features (e.g., nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall) and the target label (crop type). The remaining testing dataset (30%) was used to assess the model's performance on unseen data, ensuring its generalization to new samples.

To evaluate the performance without and with optimization of the novel RRU model, the classification metrics are validated by using the following metrics (Ismail et al., 2024).

- **Accuracy** is used to validate the proportion of correct predictions among all.
- **Precision** is defined as correctly predicted positives out of total predicted positives.
- **Recall** presented Proportion of correctly predicted positives out of actual positives.
- **F1-Score** defined a Harmonic mean of precision and recall.
- **ROC-AUC Score** is used to measure the ability to distinguish between classes.
- **Logarithmic Loss** is defined as an incorrect prediction with probabilities.
- **Cohen's Kappa (CK)** is used to compare model accuracy to a random chance agreement.
- **Matthews Correlation Coefficient (MCC)** measured the correlation between actual and predicted classifications.

RESULTS AND DISCUSSION

Result of Novel RRU model classification

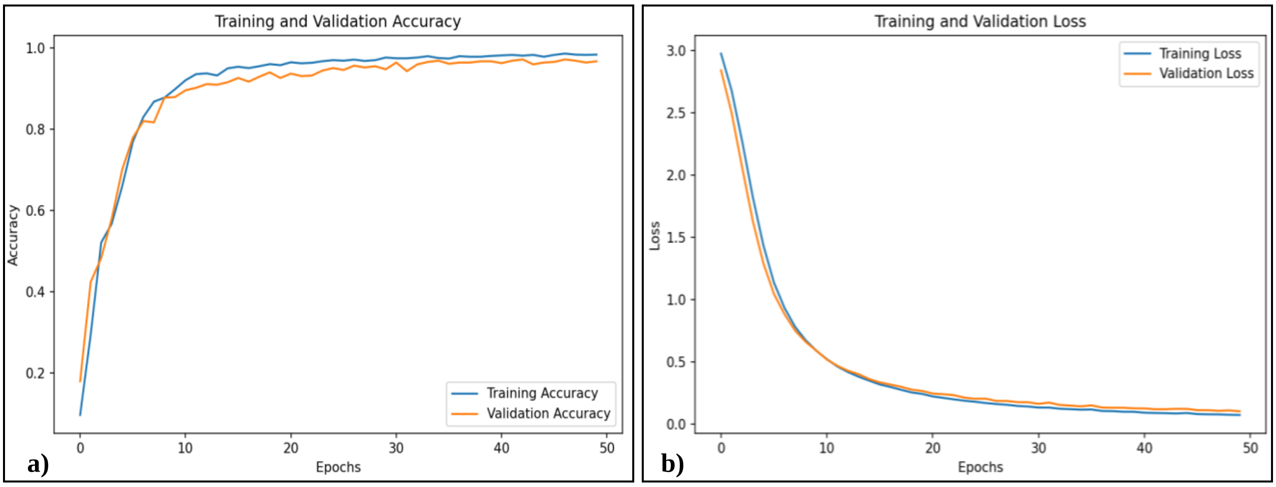

Figure 4. Novel RRU's Training and Validation Process
a) Accuracy result; b) Loss result

Figure 4a presents the Accuracy Curves on the left side, it shows the Training Accuracy curve (blue line) starts low and steadily increases reaching a plateau of around 40 epochs. Also, the Validation Accuracy (orange line) represents the validation accuracy of the RRU model that omits the dataset not used for training. It also starts low, increases, but then starts to plateau and even slightly decreases after around 25 epochs. The RRU model attains a maximum accuracy of 96.52% which is higher than all traditional methods. Also, Figure 4b, presented the Loss Curves of the RRU model with Training Loss and validation loss. Here, Training loss (blue line) shows the model's loss that starts high initially and then rapidly decreases when it reaches a minimum of around 40 epochs. Also, the Validation Loss (orange line) starts high and decreases but it starts to increase after around 25 epochs.

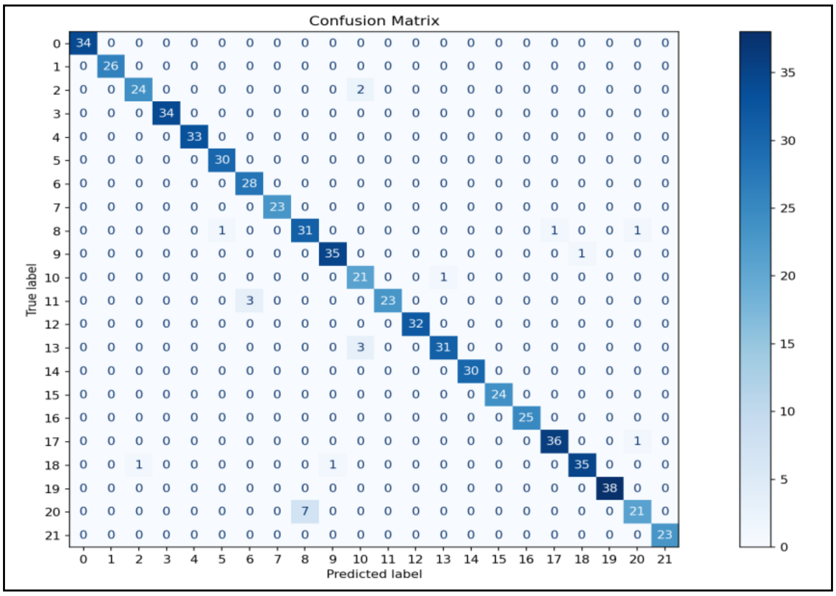

Figure 5. Confusion Matrix of novel RRU model

Figure 5 shows the confusion matrix of the novel RRU method where the diagonal elements represent the correctness of the classification result. Every diagonal cell indicates a number of instances that correctly resulted in their respective classes. For example, the top-left cell indicates that 34 instances were correctly classified as class 0 whereas, off-diagonal elements represent incorrect classifications.

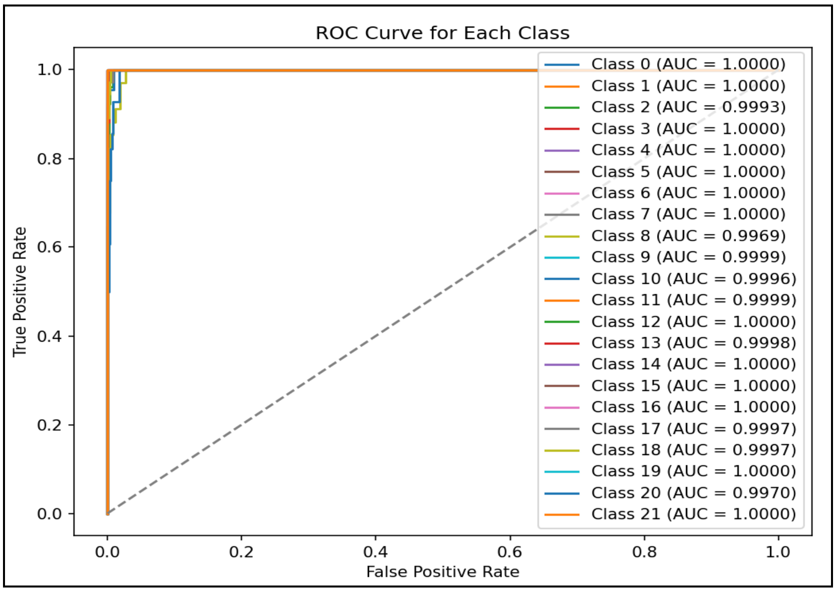

Figure 6. ROC curve of novel RRU model

The multi-class ROC curve results with AUC scores for every class is presented in Figure 6. Every line represents the ROC curve for a specific class and the AUC score indicates its performance. Here, mostly AUC has a high score that shows its strongness in performance. Also, a few classes have a lower AUC score that is also considered for further optimization.

Result of the proposed STO-RRU Model

After the tuning process of the RRU hyperparameter, the fitness curve is presented to attain an optimal solution in RRU performances. In Figure 7, the validation loss or fitness value initially fluctuates significantly but steadily decreases over iterations that show convergence to an optimal solution. From iteration 20 to 50, the fitness value steadily declined showing a proposed ability to improve the solution effectively. Beyond iteration 50, around 0.7-0.8, the curve stabilizes which shows the model has converged to a near-optimal solution. Therefore, significant improvement in fitness value and effective convergence, validating its performance is attained in it.

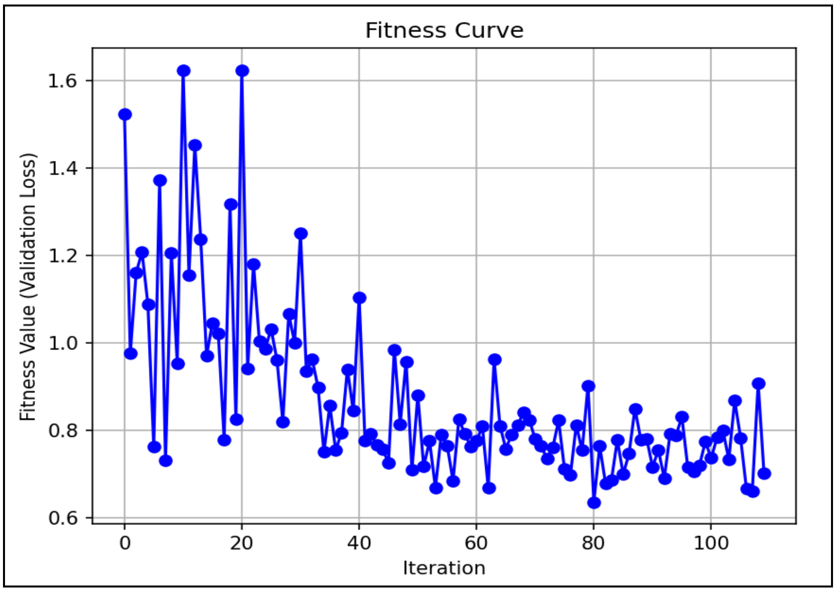

Figure 7. Fitness Curve of STO-RRU model

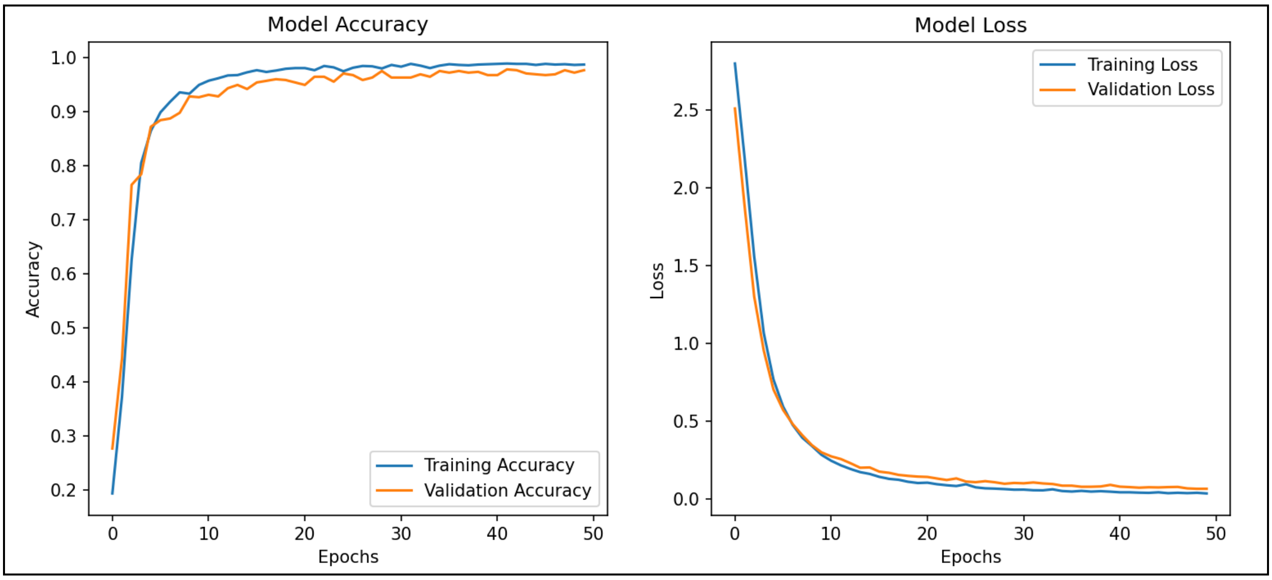

Figure 8. STO-RRU's Training and validation based on Accuracy and Loss result

Figure 8 shows the training and validation performance of a model over 50 epochs. The STO-RRU model exhibits strong performance on the training data that attains a high accuracy of approximately 98.33% and a low loss of around 0.07. it is clear that it has an effective learning of the training patterns. Therefore STO-RRU model appears to be performing well in training and validation of both accuracy and loss which is slightly better than the without optimization of the RRU model.

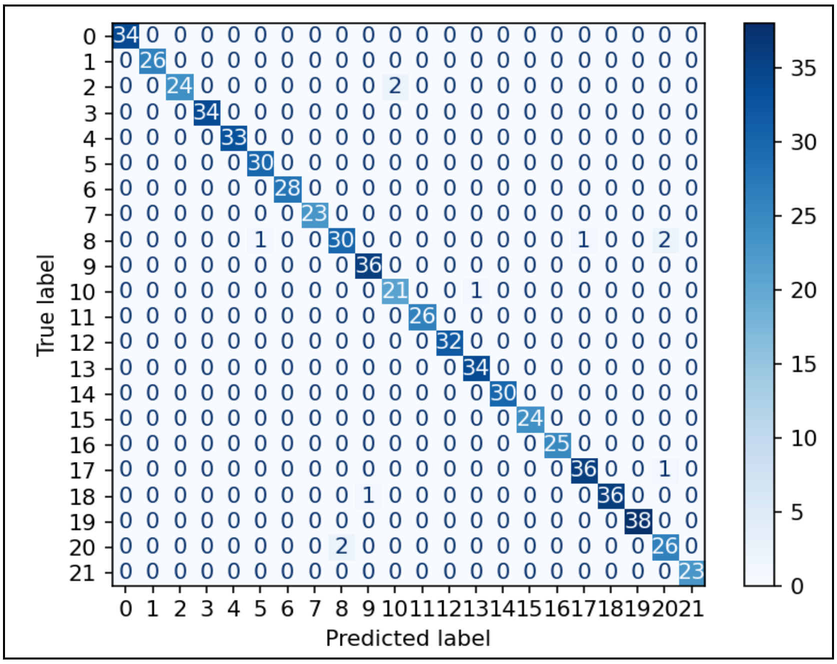

Figure 9. Confusion Matrix of STO-RRU model

Figure 9 shows the confusion matrix of STO-RRU across 22 distinct classes. The diagonal values are significantly higher the model performs well in accurately classifying samples into their correct classes. For example, for class 0, 34 samples are correctly classified, while for class 20, 26 samples are correctly classified. Also, off-diagonal entries achieved low confusion between classes.

By comparing both RRU and STO-RRU, both are strong predictions along the diagonal that indicate good overall classification accuracy. However, the STO-RRU matrix demonstrates slightly better than is shown in Table 1.

Table 1. Confusion matrix comparison with and without STO optimization in the proposed RRU model

Aspect	STO-RRU	RRU
Diagonal Values	Cleaner diagonal, more correct predictions.	Strong diagonal but slightly less accurate.
Off-Diagonal Errors	Fewer misclassifications (almost negligible).	More off-diagonal errors in some classes.
Class-Wise Performance	Higher correct classifications (e.g., class 20).	Some classes (e.g., 7, 10, 12) show misclassification.
Overall Accuracy	Higher accuracy with better optimization.	Slightly lower accuracy than STO-RRU but high among other models.

The comparison clearly showed that novel RRU performances are better than their actual ones while performing optimization like STO in it.

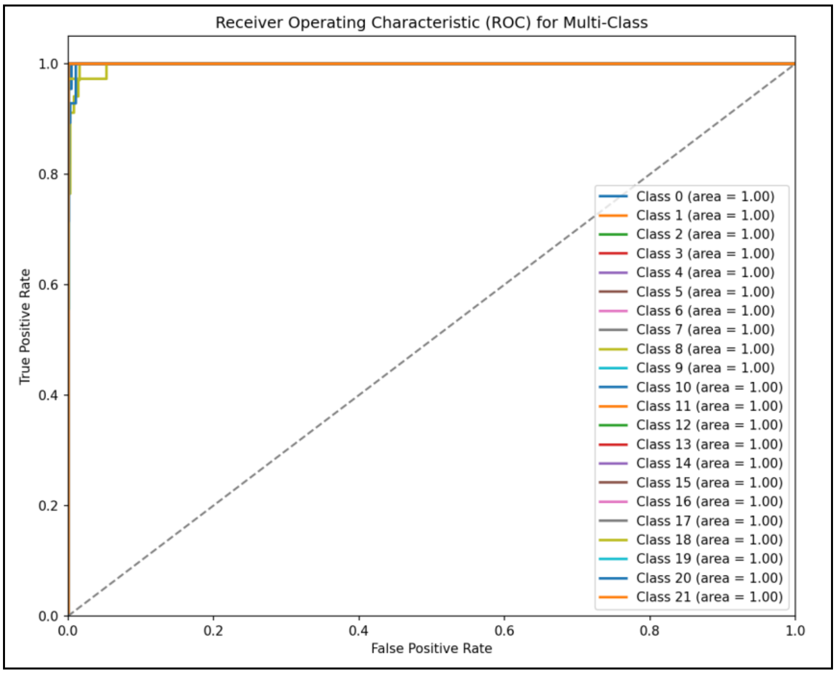

Figure 10. ROC of STO-RRU model

The ROC curve of the STO-RRU model is given in Figure 10 which shows the performance of a classification model for multiple classes. Each curve corresponds to a specific class, with the True Positive Rate (TPR) plotted against the False Positive Rate (FPR). The AUC for each class is 1.00 which indicates perfect classification performance as the model achieves ideal separation between all classes with no false positives or negatives.

Table 2. Overall performance comparison of proposed and traditional methods

Method	Accuracy	Precision	Recall	F1-Score	ROC-AUC Score	Logarithmic Loss	CK	MCC
Proposed STO-RRU	98.33	98	98	98	1	0.07	0.98	0.98
Proposed RRU (without optimization)	96.52	96.61	96.49	96.44	0.99	0.094	0.963	0.963
Bi-GRU	95.18	95	95	95	1	0.16	0.95	0.95
Bi-LSTM	93.91	94	94	94	1	0.19	0.94	0.94
Deep AR	95.3	95	95	95	1	0.14	0.95	0.95
Dense layer	95.3	96	95	95	1	0.14	0.95	0.95
VAE	50.76	51	51	50	0.94	2.42	0.48	0.48
CNN	72	66	88	75	0.75	0.65	0.44	0.47

Table 2 shows the overall performance based on various metrics for the proposed RRU with and without optimization. As a result, showing that the proposed STO-RRU model attained a better score than the Novel RRU model in all the aspects where the STO-RRU model achieved an accuracy of 98.33% and the RRU model attained 96.52%, respectively. Similarly, the STO-RRU vs. RRU performed on other metrics are precision as 98% vs. 96.61%, recall as 98% vs. 96.49%, and F1-score as 98% vs. 96.44%. Also, STO-RRU also has a higher ROC-AUC score of 1 and RRU of 0.99 where the lower logarithmic loss of STO-RRU is 0.07 and RRU is 0.094, respectively. Then the metrics of CK and MCC have a similar value on both proposed models that is 0.98 and 0.963 are attained by STO-RRU and RRU. Therefore, the proposed model RRU has an effective performance and also after performing optimization, the result has an extraordinary improvement and enhanced the model's performance effectively. Other methods like Bi-GRU, Bi-LSTM, Deep AR, and Dense layer also performed a good performance (~95% accuracy) but all these are behind the proposed optimised and without optimised RRU model. In contrast, VAE and CNN perform poorly with 50.76% and 72% accuracy, respectively.

As a result, the proposed model demonstrates its ability to classify the data accurately and correctly identifying the crop label with a minimum misclassification. Therefore, this proposed model ensured the reliability and robustness of crop recommendation suitability based on the real data.

Hardware setup

The proposed system presented a hardware setup of real-time data of environment and soil features. The proposed system integrated IoT-based sensors and proposed optimised RRU techniques for real-time crop recommendation which is shown in Figure 11. It integrates sensors for NPK levels and pH to measure essential soil parameters and also and conductivity sensor is used to monitor rainfall. An ESP8266 module with Arduino ATmega328 was used to collect and manage sensor data and an LCD display provided real-time feedback to users.

For an IoT integration, the ESP8288 accessed the Thinger.io platform for remote monitoring used to enable users to track soil and environmental data conveniently. The proposed optimized RRU model processes the collected data and then processes its advanced feature extraction and classification to recommend the most suitable crops based on its conditions. This proposed system ensured that accurate data-driven crop recommendations were effectively processed with real data to attain modern precision Agriculture 6.0.

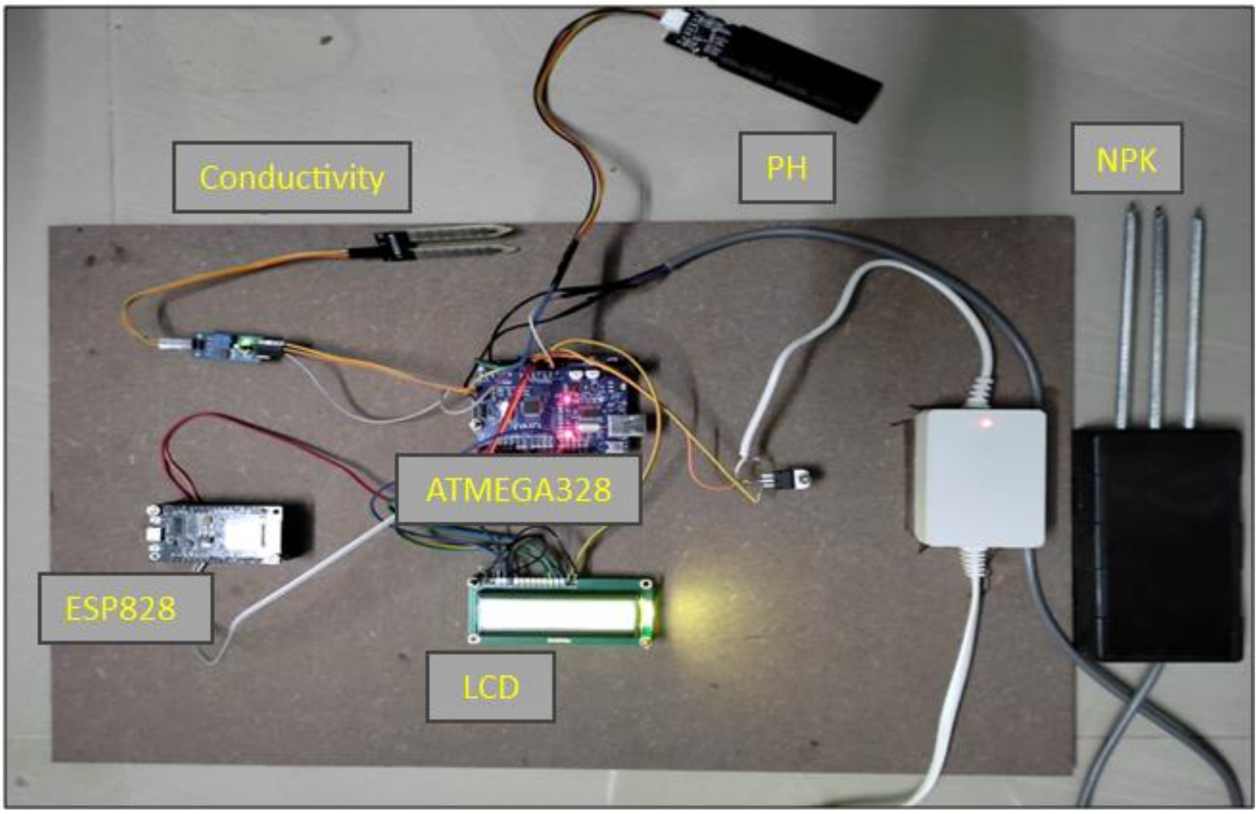

Figure 11. Hardware prototype with integration of proposed STO-RRU model

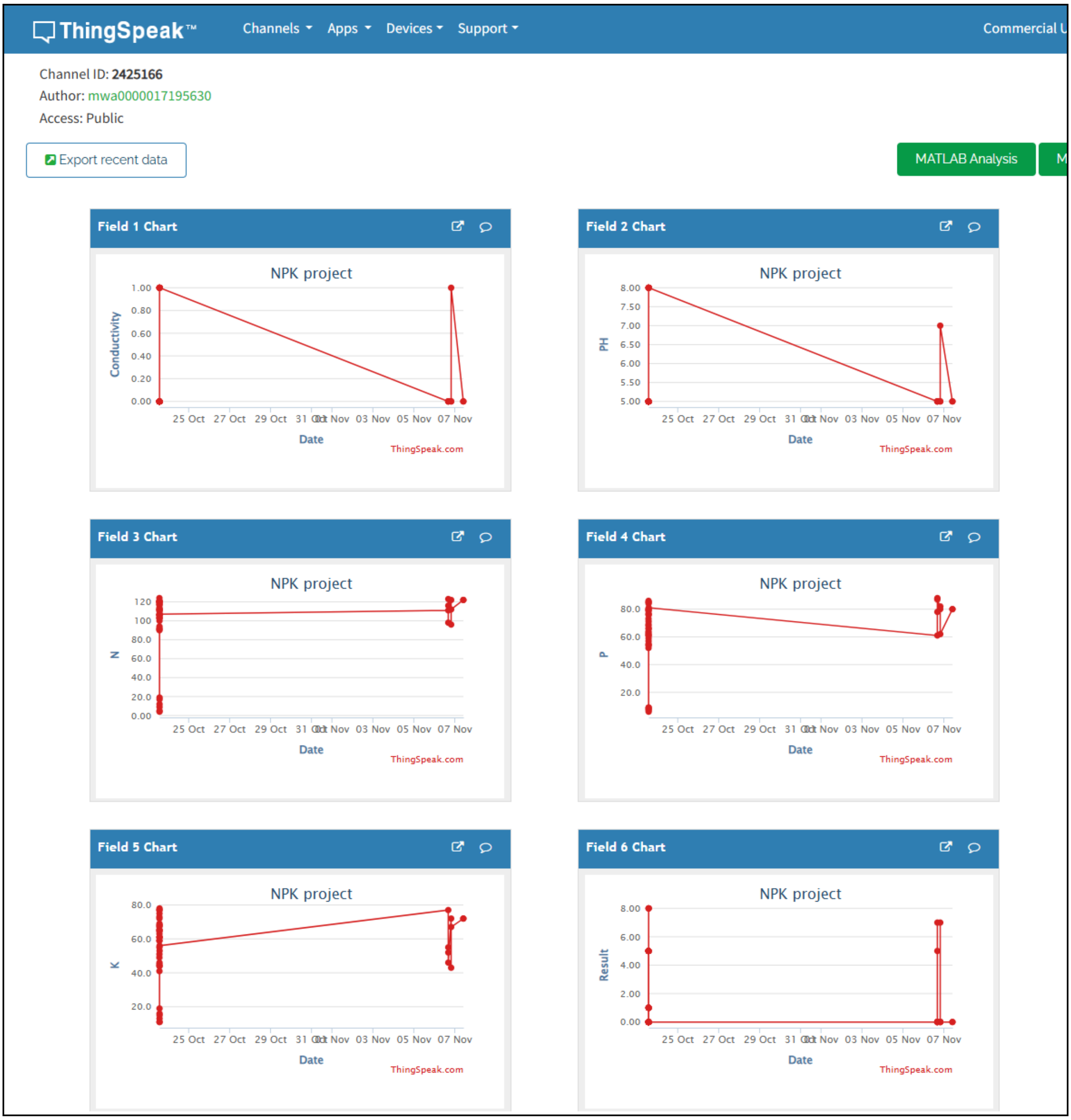

Figure 12. IoT ThingSpeak channel monitoring

Figure 12 shows a ThingSpeak channel monitoring various parameters of an NPK based on soil health. The channel tracks conductivity values between 0 and 1, pH between 5 and 8, nitrogen between 0 and 120, phosphorus between 0 and 80, potassium between 0 and 60, and moisture between 0 and 8. Based on the data, the minimization of conductivity, pH, and phosphorus levels increases the potassium levels and fluctuates the nitrogen and moisture levels. It is done by using the proposed optimised RRU model to handle a suitable recommendation. Through this system, the optimised crop growth is performed and controls the nutrient levels and monitors an environmental condition.

```
*Python 3.7.6 Shell*
File  Edit  Shell  Debug  Options  Window  Help
Python 3.7.6 (tags/v3.7.6:43364a7ae0, Dec 19 2019, 00:42:30) [MSC v.1916 64 bit
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
=========== RESTART: C:\Users\smart\OneDrive\Desktop\kitcode\app2.py ===========
URL: https://api.thingspeak.com/channels/2425166/feeds.json?api_key=8Z089PM48SLL
V57I&results=1
Received Data: {'channel': {'id': 2425166, 'name': 'NPK project ', 'latitude': '
0.0', 'longitude': '0.0', 'field1': 'Conductivity', 'field2': 'PH', 'field3': 'N
', 'field4': 'P', 'field5': 'K', 'field6': 'Result', 'created_at': '2024-02-07T1
1:04:37Z', 'updated_at': '2024-10-22T12:50:42Z', 'last_entry_id': 80}, 'feeds':
[{'created_at': '2024-11-07T05:08:26Z', 'entry_id': 80, 'field1': '0', 'field2':
 '5', 'field3': '122', 'field4': '80', 'field5': '72', 'field6': '0'}]}
 Conductivity: 0.0
 PH: 5.0
 N: 122.0
 P: 80.0
 K: 72.0
Classification result: 0
Classification result sent successfully to ThingSpeak field7.
```

Figure 13. Optimised RRU crop recommendation

Figure 13 shows the result of optimised RRU crop recommendation using real soil parameters that are explained in the following.

- **Conductivity scored as** 0.0 which shows low electrical conductivity in the soil that contains a low salt content or poor mineral composition.
- **pH scored as** 5.0 where the soil shows slightly acidic affecting nutrient availability and soil microbial activity.
- **N, P, and K scored as** 122, 80 and 72, respectively, suggesting a moderate nutrient content in the soil.

Based on these parameters, the STO-RRU model has recommended a crop that is tolerant to low conductivity and slightly acidic conditions and that has moderate nutrient requirements.

CONCLUSIONS

In this work, an accurate crop recommendation is presented with a novel RRU method to enhance Agriculture 6.0. The proposed work handles the real IoT data using sensors and wireless devices that are classified using the RRU model. The RRU model has performed a classification for N, P, K, and PH, rainfall data to analyse the soil fertility. The RRU model has implemented two new features Adaptive Scaling in the Transform Module and a Residual Connection Module that shows a unique advancement of the proposed work. The result of the proposed RRU model was validated with and without the STO model which attained a superior performance than other traditional methods. After tuning, the RRU model has an extraordinary performance with various metrics such as accuracy (98.33), precision (98), Recall (98), F1-score (98), ROC-AUC (1), Logarithmic Loss (0.07), CK (0.98) and MCC (0.98), respectively. These results established the most effective solution for crop recommendation and ensured robust learning and decision-making. This innovation and performance definitely position the RRU as the most reliable and efficient system for crop recommendation in the Agriculture 6.0 framework.

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