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Original Article

Intelligent Agronomic Advisory Model for the Prediction of Best Crop Yields

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Abstract *- Agriculture contributes approximately 40% to Nigeria's GDP, primarily driven by smallholder farmers who face challenges in standardization, decision support, and precision. This study developed an intelligent agronomic advisory model to predict optimal crop yields. Objectives included modeling farm planning workflows, presenting an intelligent agronomic model, developing a predictive system, and comparing its performance with existing systems. The study utilized analytical and empirical methodologies, employing colored petri nets and artificial neural networks for planning and prediction. The system was developed using PyCharm, Python, and MariaDB. Metrics for accuracy, speed, cost, soil pH, soil texture, and crop yield were measured. The new system achieved results of 0.25 MMRE, 600 seconds, 121.14% ROI, soil pH of 6.0, soil texture of 12-25mm, and 7.0 tons/ha crop yield, outperforming existing systems. The developed system can significantly aid smallholder farmers in enhancing crop yields, reducing poverty, and ensuring food security.*

Keywords *- Advisory, Agronomic, Artificial neural networks, Colored petri nets, Intelligent, Prediction*

1. Introduction

Agronomy, as described by Mirza [1], is essentially the art of managing farm fields, encompassing the science and economics of farmland management for crop production. Despite its significance, agronomic activities often suffer from a lack of standardization, precision, decision support, and proper planning, largely due to limited access to technology, high costs, and inadequate financial services. Smallholder farmers are particularly disadvantaged by financial limitations and a lack of knowledge about advanced farming technologies. They also face difficulties in accessing essential farm inputs like herbicides, pesticides, and fertilizers. Suppliers often struggle to connect with farmers who have specific needs, leading to inefficient resource allocation. Additionally, financial institutions and insurance companies encounter challenges in accurately determining the appropriate loan amounts or insurance coverage for farmers, resulting in repayment issues and financial crises. Traditional agricultural extension services, designed to provide information and enhance productivity, have become insufficient. Anderson and Feder [2] pointed out that these services are intended to deliver crucial information to farmers. However, Haruna and Abdullahi [3] observed that such services are now inadequate or non-existent, contributing to high poverty levels among smallholder farmers. Consequently, there is an urgent need for a system to replace the role of agricultural extension agents by offering timely and accessible information to farmers. Existing software solutions are often too expensive and complex for smallholder farmers. Therefore, there is a critical need for an affordable and user-friendly system. This research proposes the development of an Intelligent Agronomic Advisory System (IAAS) to address these challenges by utilizing Colored Petri Nets (CPN) and Artificial Neural Networks (ANN). CPN will be used to manage farm workflows, while ANN will predict crop yields and offer customized recommendations. The Intelligent Agronomic Advisory System (IAAS) will be affordable, easy to use, and portable, making it accessible even to illiterate farmers with the support of trained field agents. It will analyze factors such as farm size, crop type, soil characteristics, water needs, and climatic conditions to provide real-time, data-driven agronomic guidance. The goal is to increase crop yields, improve farm management, and enhance financial planning for smallholder farmers.By integrating Colored Petri Nets (CPN) and Artificial Neural Networks (ANN), the IAAS offers a sophisticated yet user-friendly solution to the challenges faced by smallholder farmers. The system will provide on-site, instant advice, leveraging the best agronomic practices from the industry to optimize farming operations and ensure higher yields. This innovation is expected to boost farmers' income and contribute to national food security.The

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IAAS aims to address the gaps in farm planning and operations faced by smallholder farmers. Using Artificial Intelligence (AI) to guide them through the planning process, the system will deliver immediate, location-specific agronomic solutions while considering various parameters like farm size, crop type, soil qualities, water needs, and climatic factors. By utilizing available data and best practices, the system will recommend strategies that improve yields and maximize the value of farmers' efforts. The IAAS will benefit a range of stakeholders. Smallholder farmers, as the primary beneficiaries, will receive agronomic advice that enhances farm planning and management, leading to optimal farm inputs and improved yields. Government agencies, financial institutions, input suppliers, and insurance companies can also use the system to determine the appropriate support to offer farmers, reducing guesswork and minimizing conflicts.

The IAAS will operate by collecting inputs from farmers, analyzing data against standard agronomic practices, and providing real-time recommendations. This approach will allow farmers to plan effectively, know the expected yield, and guide their activities without exceeding their budgets. Stakeholders will also be able to make informed decisions, leading to better yields and planning methods, ultimately promoting income generation for farmers and national food security. By combining CPN and ANN, the IAAS will offer a cutting-edge solution to enhance smallholder farming operations. The system will ensure efficient farm workflow management through CPN and provide predictive modeling through ANN. This technological approach is crucial for modernizing agriculture, keeping it aligned with global advancements, and supporting human survival and prosperity through increased agricultural productivity.

2. Literature Review

Dahiya et al. [4] describe computational intelligence as a set of adaptive mechanisms that enable intelligent decision-making in complex and dynamic environments. This includes techniques like Neural Networks (NN), Evolutionary Computing (EC), Swarm Intelligence (SI), Fuzzy Systems (FS), reinforcement learning, and combinations of these approaches. For intelligent systems to function effectively, they must be capable of data analysis, recognizing relationships between events or objects, executing meaningful actions, and adapting to changing conditions. These systems also need features like fault tolerance, self-organization, self-correction, adaptability, mobility, and distributed networking. Klump [5] characterized intelligent systems as computer-driven decision-making processes that are transforming industries such as manufacturing, security, and logistics by improving quality, adaptability, and energy efficiency. These systems integrate advanced technologies like artificial intelligence, cybersecurity, deep learning, natural language processing, embedded CPUs, distributed storage, wireless networking, and graphical signaling. Beemer and Gregg [6] emphasized that advisory systems support decision-making in unstructured situations without offering a single correct answer. These systems provide recommendations to aid the decision-making process while the final choice remains with the human user. They work in collaboration with humans to identify problems and iteratively assess potential solutions. Petri nets, as defined by Peterson [7], are bipartite directed graphs consisting of transitions, places, and directed arcs used to model the dynamic behavior of systems through states and state changes. Hasan and Ali [8] further explain that petri nets are valuable tools for describing and analyzing information and control flow in systems characterized by asynchronous and concurrent activities. Artificial neural networks (ANNs) are highly effective tools for predicting crop yields and improving agricultural outcomes.

For example, Snehal et al. [9] developed a feedforward backpropagation ANN for crop prediction by analyzing soil and atmospheric characteristics. Panda et al. [10] used vegetation indexes and data mining techniques to enhance the accuracy of crop yield forecasts. Nevavuori et al. [11] applied deep Convolutional Neural Networks (CNNs) using RGB and NDVI data from UAVs for yield prediction, crop detection, weed identification, and biomass evaluation. Khaki et al. [12] employed a hybrid CNN-RNN model for crop yield prediction, demonstrating superior performance compared to other methods. Farm planning operations, which involve multiple concurrent processes, benefit significantly from being modeled with petri nets. Kristensen [13] highlighted the advantages of such modeling, including better insights into design and operations, ensuring completeness, and identifying errors.

In this study, colored petri nets were utilized to manage farm process workflows. Shramenko et al. [14] pointed out that petri nets simplify the modeling of complex problems by accounting for random factors, thereby reducing the chances of errors and failures. Guan et al. [15] applied hybrid petri nets to model farm workflows in agricultural production, with a focus on resource allocation and process simulation in uncertain environments. Their model aimed to optimize farm work planning and resource distribution. Similarly, this study used colored petri nets to simulate farm process workflows. Siti et al. [16] reviewed the application of Artificial Neural Networks (ANN) in crop yield prediction, noting their effectiveness in interpreting crop variability. Although their research differs from this study, it provided valuable insights for predicting crop yields for smallholder farmers using ANN. Liu and Heiner [17] proposed using colored petri nets for modeling and simulating large biological systems, a method also employed in this research for managing farm process workflows. Balakrishnan [18] demonstrated the utility of combining ANN and colored petri nets by predicting damage and simulating repairs in water distribution systems. This is analogous to this study's use of these tools in the agricultural sector to enhance productivity. Abdulbasit et al. [19] conducted a study on predicting farm yields using machine learning techniques like decision tree classifiers, random forests, and support vector machines. They found that predictions in the Southeast region were most accurate, with a prediction accuracy of 138.9%. However, their study lacked clear definitions of variables and primarily focused on location-specific predictions with limited evaluation metrics. Elbasi et al. [20] explored the integration of machine learning algorithms in agriculture to optimize crop production and reduce waste. Their study highlighted the challenges and opportunities in current agricultural machine learning applications and reported high classification accuracy (up to 99.59%) using algorithms such as Bayes Net and Naïve Bayes Classifier. They emphasized the importance of incorporating real-time IoT sensor data for improved farming decisions but identified a gap in farm planning and management guidance. Bhagat et al. [21] examined crop yield prediction using various machine learning algorithms, including Random Forest Regressor, Decision Tree Regressor, Linear Regression, and LSTM. They found that Random Forest Regressor and Linear Regression were the most accurate for crop yield prediction. Although their study contributed to bridging technology and agriculture for better decision-making on future crops, it did not address farm planning workflows. It was limited in the variables considered, such as fertilizer and land size. Computational intelligence employs techniques such as Artificial Neural Networks (ANN) and Petri nets.

It is essential across numerous industries, especially in agriculture, where it contributes significantly to crop prediction and yield optimization. These technologies support smart decision-making, efficient resource management, and improved system performance, helping to navigate the complexities of dynamic and challenging environments.

3. Materials and Methods

This study utilizes both analytical and experimental approaches, combining Colored Petri Nets (CPN) and a multilayer perceptron feedforward Artificial Neural Network (ANN) to optimize farm planning and management workflows in crop cultivation. The model's effectiveness is assessed using the Petri Nets Simulator for CPN analysis and PyCharm, along with other Python tools, for evaluating the ANN. Key performance indicators include mean, accuracy, cost (return on investment), time, soil pH, texture, and crop yield. The ANN model, trained through supervised learning and backpropagation, achieved accuracy by minimizing the mean absolute error.

3.1. Architecture of the Proposed System

The architecture of the proposed system is given in Figure 1. The proposed design of the intelligent agronomic advisory system is illustrated in Figure 1. The system comprises key components, including the User, Knowledge Base, Intelligent System Shell, and Standard Crop Yield Data.

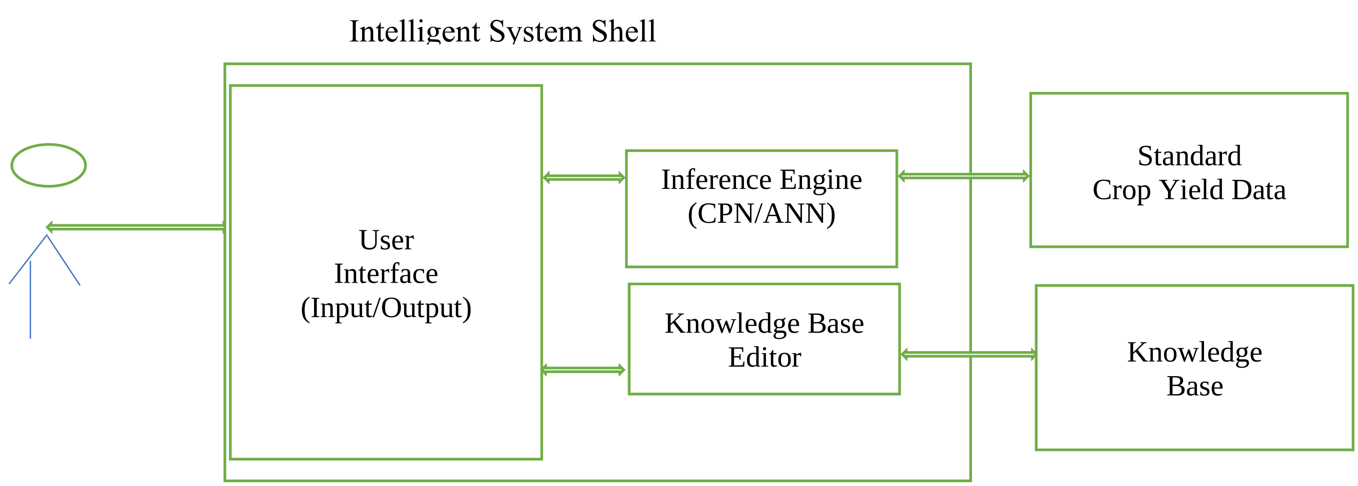

Fig. 1 Intelligent agronomic advisory system architecture

3.2. Farm Process Modeling and Workflow with Colored Petri Nets (CPN)

In this study, an Artificial Neural Network (ANN) is employed for neural network training to enhance agricultural yields. Colored Petri Nets (CPN) are used to model the workflow management of farm operations.

In this research:

- *Circles (Places):* Represent resources used in farm activities, such as tractors, hoes, and cutlasses.
- *Rectangles (Transitions):* Represent farm processes like site selection, tilling, weeding, planting, and others.
- *Arrows (Arcs):* Indicate the direction of workflow execution within the petri nets.
- *Black Dots (Tokens):* Indicate the quantity of resources available at a particular place, with each token representing one resource.

These elements are used to illustrate farm management processes like site selection, tilling, planting, weeding, irrigating, fertilizing, and harvesting in Figure 2.

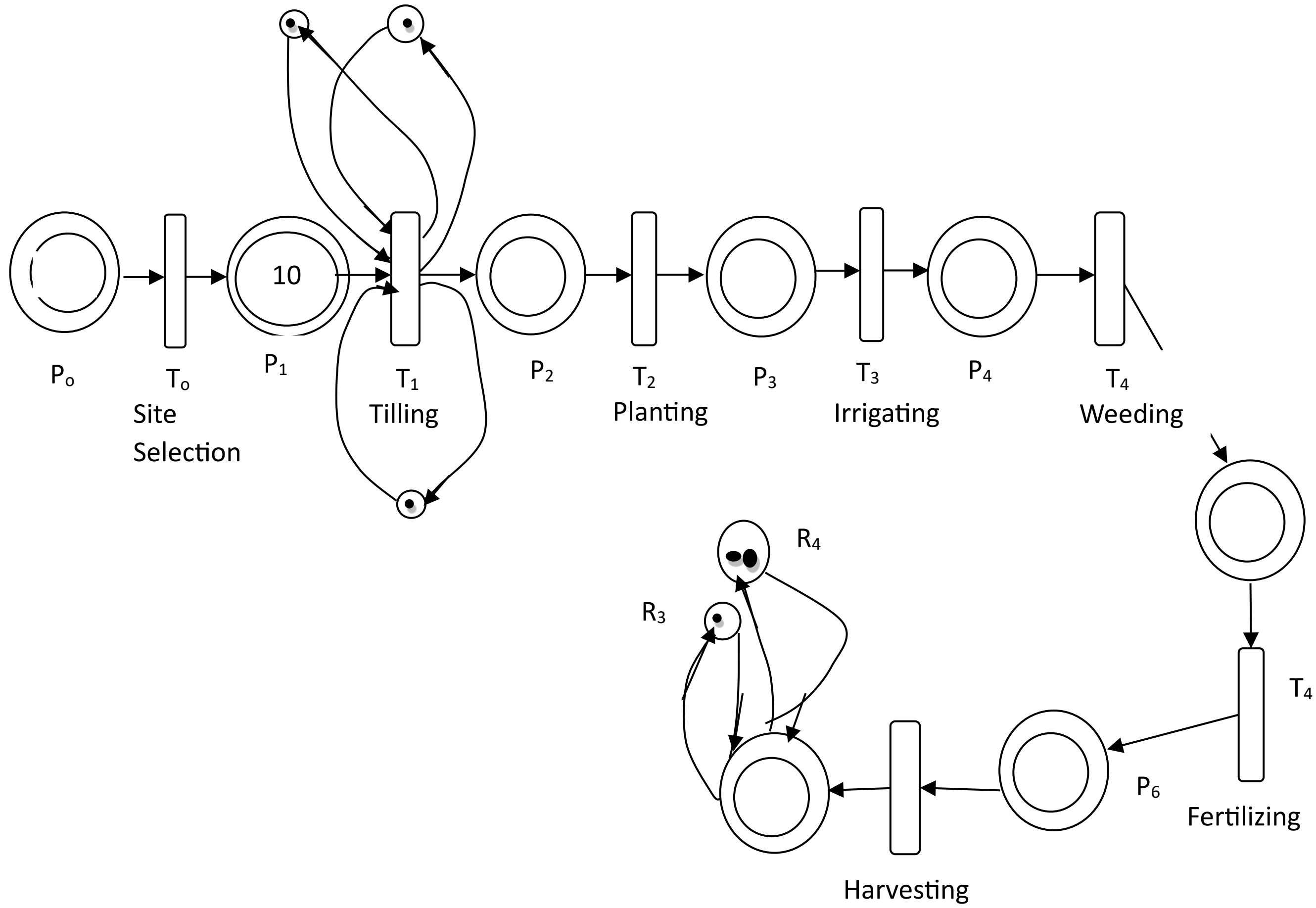

Fig. 2 Workflow Management of Farm Processes in Colored Petri Net Representation

A model for simulating the workflow on a single farm is provided in Figure 2, illustrating the crop production process using specific resources. The diagram features continuous places (Pi) and transitions (Ti), where Ti represents the state of the farmland and the progress of farm operations. Discrete places (Pi) depict the status of resources like workers and tractors, each linked to a time window to ensure operational timeliness.

Initially, the token in P1 indicates that the farmland is ready for tilling after the successful site selection. As work progresses using resources R1, R2, and R3, the value in P1 decreases while the value in P2 increases. Once tilling is complete, the token in P1 drops to a low level, and in P2, it rises to a high level, signifying that resources are now available for other tasks. This study uses Colored Petri Nets (CPN) to simulate the agricultural workflow. The model represents both discrete and continuous farming activities, such as site selection, tilling, planting, irrigating, weeding, fertilizing, and harvesting. Each activity must meet criteria such as timeliness, the availability of farmland, machinery, and personnel. As each farm task is completed, the workflow transitions, releasing resources like labor and machinery for subsequent tasks. In the proposed CPN model:

- *Transitions (rectangles):* Represent agricultural tasks.
- *Tokens (black dots):* Represent resources like labor or machinery.
- *Places (circles):* Represent the status or condition of a farm or resource.

The remaining sections are discrete, while the continuous component includes transitions related to agricultural activities and places corresponding to farmland. Resources, agricultural equipment, and uncertainties such as equipment failure are treated as discrete elements.

3.3. Prerequisites for the Efficient Execution of Colored Petri Nets in Farm Planning Workflow

To manage the farm process workflow using CPN, resources must be allocated to specific places, and the firing order of transitions must be determined. The following guidelines can be applied for resource allocation and the execution of transitions in CPN for farm management.

3.3.1. Site Selection (March - April)

- The soil must be favorable for the crop.
- Climatic conditions must be suitable for the crop.
- Farm size must support the expected yield.

- Resources like measuring tapes and pegs must be available.

3.3.2. Tilling (May - July, crop-dependent)
- Resources for tilling must be available.
- Timing must align with the cropping season.

3.3.3. Planting (April - July)
- Seeds must be available.
- Resources for planting must be available.
- Planting must occur early enough to ensure positive outcomes.

3.3.4. Irrigating (as required)
- A water source must be available.
- The justification for irrigation must be clear.
- Timing for irrigation must be appropriate.

3.3.5. Weeding (as required)
- Resources for weeding must be available.
- Sufficient weeds to be removed.
- Timing (early or delayed) must be considered.
- Weeding can be controlled or uncontrolled.

3.3.6. Fertilizing (May - September, crop-dependent)
- Fertilizer products must be available.
- Tools for fertilizer application must be available.
- The soil must be in a favorable condition (moist).
- Crops must be at the right age for fertilizing.

3.3.7. Harvesting (July - December)
- The crop must be ripe.
- Resources for harvesting must be available.
- Storage facilities must be available.

3.4. Model of the Colored Petri Net

According to David and Alla [22], the essential relationship of petri nets is as follows:

$$m = m_0 + W.\ s \tag{1}$$

where

current marking of places is denoted by m,
incidence matrix represented by W, and
characteristics vector is given by s.

In this study, the farm work allocation model considers the following variables: t_i (the duration of the farm work), r_i (the resources required for the task), and m_i (the area of farmland, which represents the marking of locations in the petri nets model). The resource speed is denoted by $V_{ri,}$ and the combination of r_i and t_i can be used to form the incidence matrix, W. Consequently, the following equation will apply for the use of tools and machinery:

$$m_k = [t_k^{r1}(e) - t_k^{r1}(s)]V^{r1} + [t_k^{r2}(e) - t_k^{r2}(s)]V^{r2} + \ldots + [t_k^{rh}(e) - t_k^{rh}(s)]V^{rn}- \tag{2}$$

Based on the above, $t_{irj(s)}$ represents the start time of a resource, r_j indicates its role in farm operations, and $t_{irj(e)}$ denotes its finish time. Equation (2) is used to construct the incidence matrix for a sequence of tool and machinery usage. In this process, vectors representing the agricultural area (m) and velocities (V) are transposed, and their product calculates the amount of time each resource is used during a particular farm operation. This approach applies to all farm management tasks considered in the study, including site selection, tilling, planting, irrigation, weeding, fertilizing, and harvesting for specific crop varieties at designated sites.

3.5. Modeling the Artificial Neural Network for Predicting Crop Yield

To estimate crop yields, this study employed a multilayer perceptron feedforward Artificial Neural Network (ANN) model utilizing backpropagation, a supervised learning technique in machine learning. According to Jordanov [23], the ANN can be mathematically represented as follows:

$$X = \sum_{i=0}^{n} Wixi + \mathrm{B} \tag{3}$$

where

W_i = weights, x_i = inputs, n = number of inputs, B = bias and X = Output(s). The ANN model is composed of three essential layers: the input layer, the hidden layer, and the output layer. Data related to farm size, crop type, soil characteristics (such as pH and texture), crop water needs, and climatic factors (including temperature and absolute humidity) are fed into the input layer. The hidden layer processes this information and functions as a black box, with the output layer receiving the processed results. Figure 3 illustrates the ANN representation. The inputs to the advisory system, labeled x_1 through $x_{5,}$ along with their corresponding weights, are illustrated in Figure 3. In addition to the weighted sum of these inputs, a bias factor is included to adjust the final result. The inputs encompass farm size, crop type, soil pH and texture, the water requirements for the crop, and climatic factors such as temperature and humidity. The output of the ANN model, denoted as Y, represents the predicted crop yield.

To accurately predict crop yield, the study employs the following steps:

Step 1: Defining Variables
- *Independent Variables:* Size of the farm, amount of water needed, climatic elements (temperature and humidity), and soil characteristics (texture and pH).
- *Dependent Variable:* Expected yield.

Step 2: Collection of Data
- Data is sourced from institutions like NIMET, FAO, BNARDA, and the University of Agriculture, Makurdi. It includes numerical values for crop yield and climatic data such as temperature and absolute humidity, which are crucial for yield prediction.

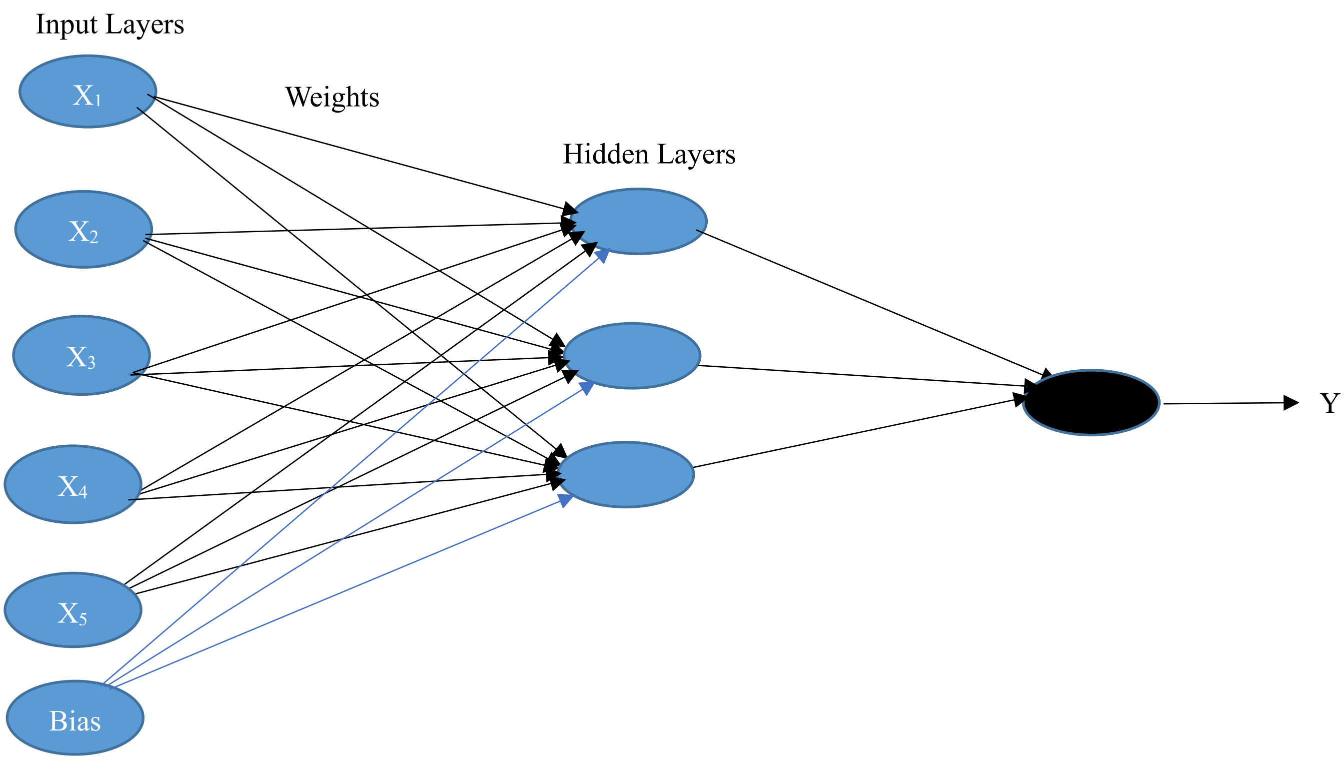

Fig. 3 Intelligent Agronomic Advisory System ANN Diagram

Step 3: Normalization

- Data is normalized using the min-max approach to prepare it for neural network training. The formula for min-max normalization is:

$$y = (x\text{-}min) / (max\text{-}min) \quad (4)$$

Where X is the collection of observed values for x, and min and max are the lowest and maximum values in X. One can readily observe that if x = min, y = 0, and if x = max, y = 1. This indicates that the whole range of values in X, from min to max, is mapped to the range 0 to 1. The least value in X is mapped to 0, and the largest value in X is mapped to 1.

Step 4: Data preprocessing

Data preprocessing aims to adjust the input variables and the distribution of network parameters. This study uses Principal Component Analysis (PCA) to reduce the dimensionality of the input space. PCA applies a linear transformation to convert an N-element vector x into a k-element vector y, using the matrix:

$$W \in R^k \times R^N: y = Wx \quad (5)$$

In this case, the autocorrelation matrix for x's eigenvectors makes up W.

Step 5: Training, Testing, and Validation Sets

Data is divided into three sets. They are:

- Training: 60%
- Testing: 20%
- Validation: 20%

Key hyper-parameters for the neural network include:

- *Learning Rate:* A decaying rate is used to balance optimization and generalization.
- *Momentum:* Set at 0.7 to help avoid oscillations.
- *Number of Epochs:* 400 epochs for training.
- *Batch Size:* Default size of 10.

Batch gradient descent is employed for its computational efficiency and convergence properties. The update rule is:

begin w: = w_0
While $||\nabla f(w)||2 > \epsilon$ do
W: = w-α. ∇f(w)
End
where f = function, w = vector.

Step 6: Design of the Neural Network

- *Hidden Layers:* One hidden layer with three neurons, chosen based on rules to avoid overfitting and underfitting.
- *Transfer Function:* Sigmoid function is used for its non-linearity and differentiability:

$$\sigma(X) = 1/1\text{-}e^{-\lambda x} \quad (6)$$

Step 7: Evaluation of the Neural Network

The network's performance is evaluated using the Mean Absolute Error (MAE):

$$MAE = \sum_{i=1}^{n} (|yi - xi|)/n \quad (7)$$

Where yi is the predicted value, xi is the actual value, and n is the total number of data points. If the error is significant, backpropagation is used to adjust the weights and minimize the error. The error gradients for the output and hidden layers are given by:

$$dE/dW_{ijk} \tag{8}$$

- *Output Layer:*

$$dE/dW_{jk} = (O_j)\delta_k \tag{9}$$

where $\delta_k = O_k(1-O_k)(O_k-t_k)$.

- *Hidden Layer:*

$$dE/dW = O_i\delta_j \tag{10}$$

where $\delta_j = O_j(1-O_j) \sum_{k\epsilon k}\delta_k W_{jk}$.

Step 8: Training of the Neural Network

The backpropagation algorithm is a widely used method for supervised learning, employed to train neural networks. To improve accuracy, this algorithm adjusts the network's weights based on prediction errors. The process involves the following steps:

i. *Forward Propagation:* Calculate the network's output using the current weights and input data.
ii. *Error Calculation:* Measure the difference between the predicted output and the actual target values.
iii. *Backward Propagation:* Propagate the error backwards through the network to compute the gradients of the weights.
iv. *Weight Update:* Modify the weights in the direction that minimizes the error based on the gradients.

Step 9: Neural Network Implementation for the Crop Yield Prediction System

The study successfully implemented a neural network-based crop yield prediction system using the Python programming language in the PyCharm environment. Key implementation steps include:

1. *Data Input:*
- Inputs such as farm size, crop type, soil pH and texture, temperature, humidity, and rainfall are utilized.
- These inputs are normalized using the min-max method to scale values between 0 and 1.

2. *Forward Propagation:*
- Data is processed through the network with applied weights.
- The sigmoid function is used as the transfer function to compute the output.

3. *Output Interpretation:*
- The output represents the predicted average crop yield.
- A below-average result indicates a poor yield and provides recommendations to address the issues.
- An above-average result suggests a likely good yield, with additional recommendations for further optimization if necessary.

The intelligent agronomic advisory system (IAAS) relies on a rule-based table for accurate yield prediction. Crops are classified into categories such as cereals, legumes, roots/tubers, and vegetables. The rules are based on climatic conditions, water needs, and soil properties, as outlined in Table 1.

Table 1. Intelligent agronomic advisory system decision rules

S/No	Crop Type	Factor	Value Range	Conditions
1	Cereals	Temperature (°C) Humidity (kg/m ^{3}) Soil pH Soil Texture (m) Water need (mm)	31 to 33 72 to 81 6.0 to 7.0 0.12 to 0.55 110 to 220	If temperature lies between 31 and 33, humidity lies between 72 and 81 soil pH lies between 6.0 and 7.0, soil texture lies between 0.12 and 0.55 and water requirement is between 110 and 220, then yield is good.
2	Legumes	Temperature (°C) Humidity (kg/m ^{3}) Soil pH Soil Texture (m) Water need (mm)	27 to 33 27 to 33 5.5 to 7.5 0.12 to 0.55 110 to 220	If temperature lies between 27 and 33, humidity lies between 27 and 33, and soil pH lies between 5.5 and 7.5, soil texture lies between 0.12 and 0.55 and water requirement is between 110 and 220, then yield is good.
3	Roots & Tubers	Temperature (°C) Humidity (kg/m ^{3}) Soil pH Soil Texture (m) Water need (mm)	27 to 33 72 to 81 6.0 to 7.5 0.10 to 0.55 110 to 220	If temperature lies between 27 and 33, humidity lies between 72 and 81, soil pH lies between 6.0 and 7.5, soil texture lies between 0.10 and 0.55, and water requirement is between 110 and 220, then yield is good.
4	Vegetables	Temperature (°C) Humidity (kg/m ^{3}) Soil pH Soil Texture (m) Water need (mm)	27 to 34 72 to 81 6.0 to 7.5 0.10 to 0.55 110 to 220	If temperature lies between 27 and 34, humidity lies between 72 and 81, soil pH lies between 6.0 and 7.5, soil texture lies between 0.10 and 0.55, and water requirement is between 110 and 220, then yield is good.

The data presented in Table 1 were sourced from reputable agronomic research institutions, centers, and literature that have undergone thorough testing to establish their significant impact and effectiveness on agronomic practices.

3.6 Intelligent Agronomic Advisory System Model

The intelligent agronomic advisory system model is formed from equation (3). Thus, we have:

$$X = \sum_{i=0}^{n} Wixi + \mathrm{B} \quad (11)$$

That is;

$$\mathrm{Y} = \sum_{i=0}^{n} Wixi + \mathrm{B} \quad (12)$$

where w represents the variable weights, n is the number of variables, xi denotes the variables, B is the network bias, and Y is the expected yield. Equation 12 illustrates the proposed system model along with its specified parameters. Moving forward, the intelligent agronomic advisory system will be built upon this framework. The model's evaluation now provides the predicted crop yield, represented as numerical values in tonnes per hectare (tons/ha).

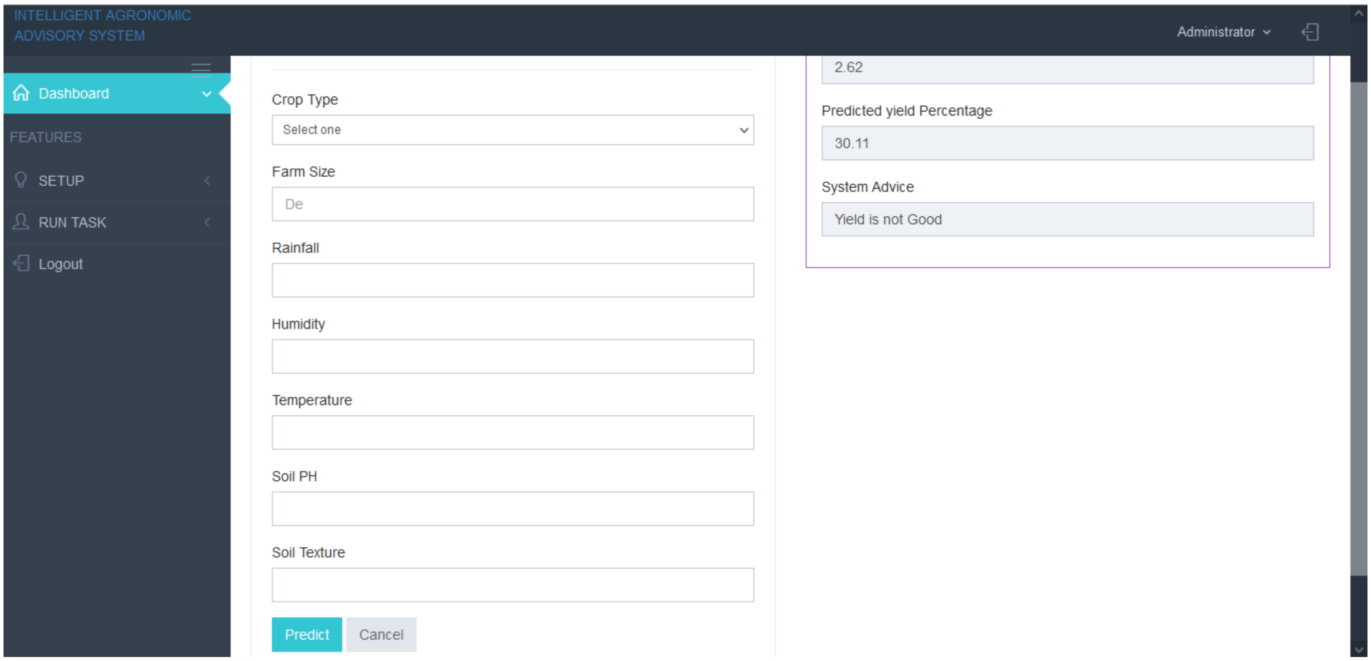

Fig. 4 ANN submenu

4. Results and Discussions

4.1. System Menus

Figure 4 displays the choices for putting the suggested system into practice. The ANN forecasts the crop yield for cassava cultivation based on specific crop conditions. It provides an estimated yield, its percentage, and relevant recommendations. These results are compared with standard cassava values and benchmarked against the Mean Absolute Error (MAE) of 5903 from the network training. Yields falling below the MAE are classified as poor, while those meeting or exceeding the MAE are considered good. This comparison assesses the quality of the yield.

4.2 Results

The farm processes planning workflow was modeled using colored petri nets, where tokens represented resources and conditions that triggered farm processes. This system, known as the Intelligent Agronomic Advisory System (IAAS), integrates an artificial neural network to forecast crop yields, offer advice for enhancing yields, and boost investor confidence by estimating potential returns. The newly developed IAAS achieved the following metrics for cassava cultivation: accuracy of 0.200, processing time of 600 seconds, cost (return on investment per hectare) of 121.14%, soil pH of 6.0, soil texture of 12-25mm, and a crop yield of 7.0 tons/ha. These results show improvement compared to previous methods, which had an accuracy of 0.54, processing time of 1800 seconds, cost (return on investment per hectare) of 50%, soil pH of 6.5, soil texture of 25mm, and a crop yield of 4 tons/ha. The neural network's performance was evaluated with a mean absolute error (MAE) of 5903, which is slightly below the standard cassava yield of 8.7 tons/ha, indicating an effective prediction of cassava yield in Nigeria.

4.2.1. Interface of Colored Petri Nets (CPN) Simulator

The Colored Petri Nets (CPN) model was assessed using the Petri Nets Simulator, a free Windows-compatible application. This simulator offers a graphical user interface with tools for creating, simulating, viewing, and analyzing CPN models, allowing users to edit and analyze colored petri nets effectively. Figure 5 shows the interface of the Petri Nets Simulator.

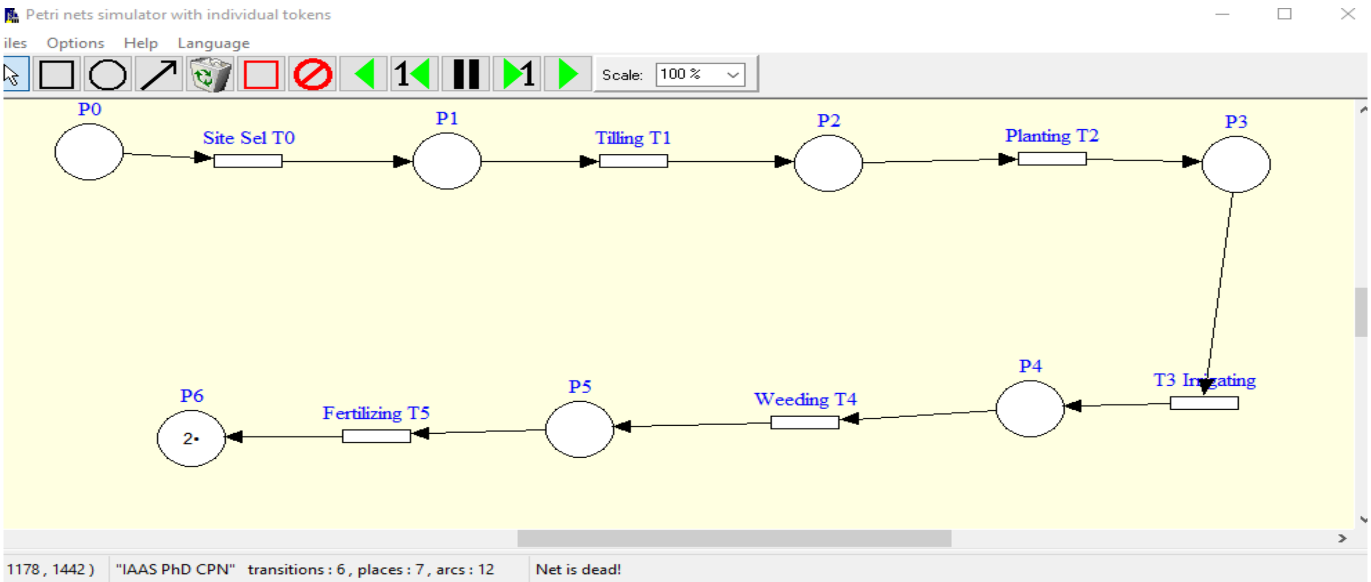

Fig. 5 Petri Nets Simulator Interface

4.2.2. Training the Artificial Neural Network (ANN) in the Python Environment

The ANN model was trained using Python within the PyCharm environment, which supports various development libraries. The training dataset included climatic data (temperature, humidity, and rainfall) from NIMET and the Makurdi Weather Station, covering the period from 1960 to 2020 for specific months. Soil data (pH and texture) was collected from ten locations around Makurdi, Benue State, with six samples per site. In total, the dataset consisted of 240 samples, with 60% allocated for training (144 samples) and 20% each for testing and validation (48 samples). Figures 6 and 7 display the dataset's network training screenshots.

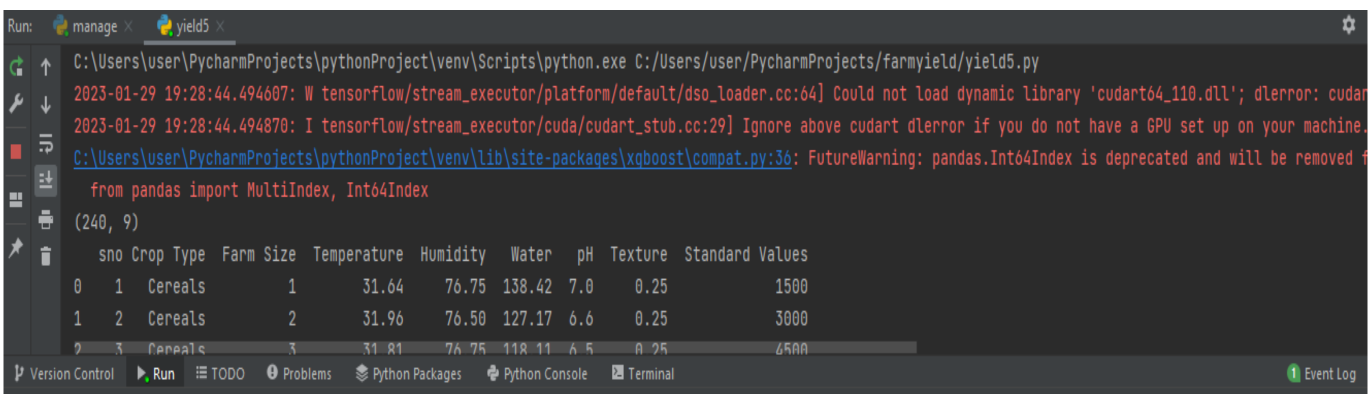

Fig. 6 Network Training Initialization

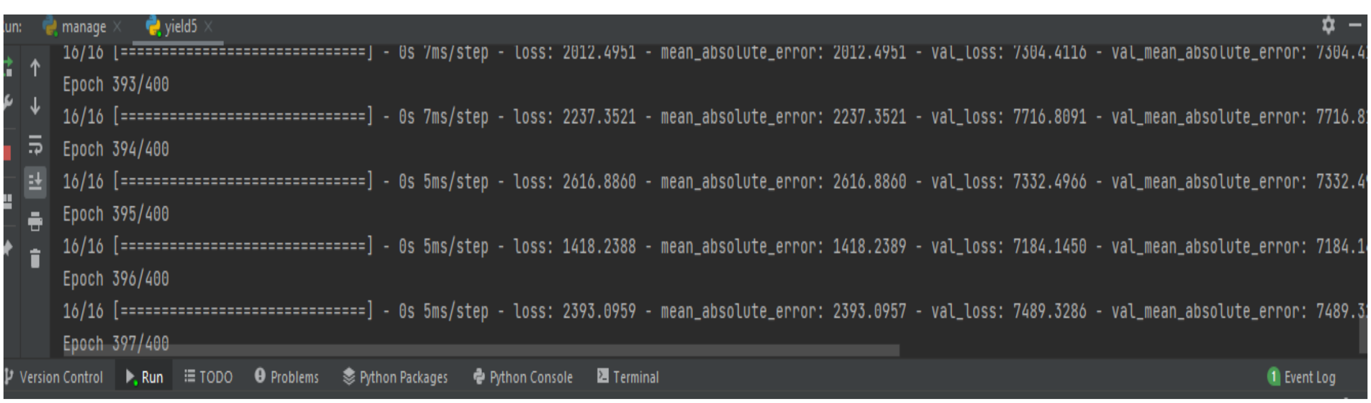

Fig. 7 Network Training at Epochs and Showing Accuracy Measures

The ANN model was trained using Python within the PyCharm environment, which supports various development libraries. The training dataset included climatic data (temperature, humidity, and rainfall) from NIMET and the Makurdi Weather Station, covering the period from 1960 to 2020 for specific months. Soil data (pH and texture) was collected from ten locations around Makurdi, Benue State, with six samples per site. In total, the dataset consisted of 240 samples, with 60% allocated for training (144 samples) and 20% each for testing and validation (48 samples).

The graph in Figure 8 illustrates that the training and validation curves are nearly aligned, suggesting that the model is not overfitting. This closeness indicates that the training results are dependable and that the loss function is functioning effectively. Figure 9 displays a graph of Mean Absolute Error (MAE) against epochs, showing that the network's MAE was approximately 5903. This MAE value reflects the strong performance and accuracy of the model, being slightly below the actual cassava yield of 8.7 tons/ha. The Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and MAE values obtained are as follows:

1. Mean Absolute Error (MAE): 5902.8
2. Mean Squared Error (MSE): 168,127,380.6
3. Root Mean Square Error (RMSE): 12,966.4

The MAE value of 5903 indicates a minimal error in the ANN's predictions for cassava yield, as it closely matches the actual yield of 8.76 tons/ha. The system's performance evaluation involves analyzing factors such as soil pH and texture, cost (return on investment), prediction accuracy, evaluation time, and yield and comparing the system's predictions to actual values. The cassava crop was used for both the experiment and evaluation and the results of the previously developed systems were compared with those of the newly designed IAAS. This information is detailed in Table 2.

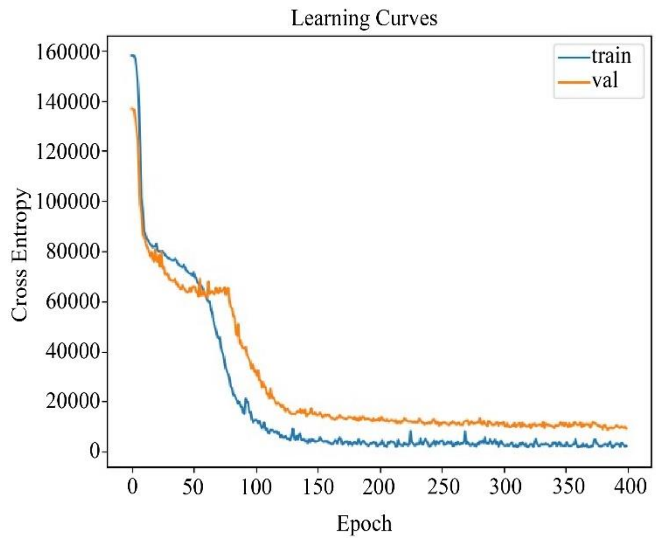

Fig. 8 Cross Entropy (Loss Function) vs. Epoch Graph

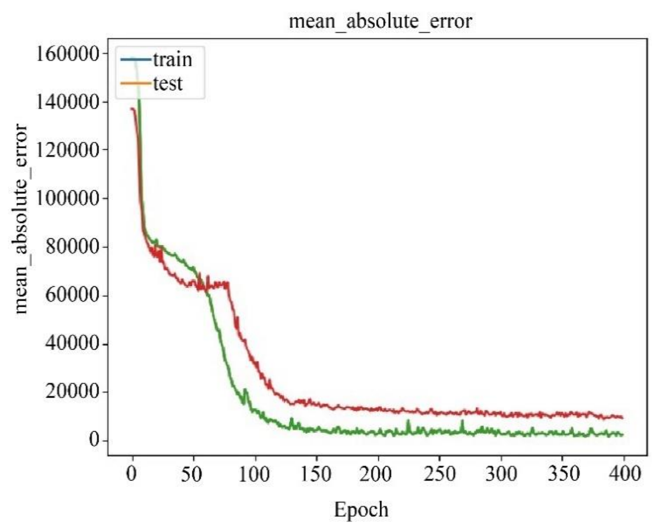

Fig. 9 Mean Absolute Error versus Epoch Graph

Table 2. An Evaluation of the Existing Systems and IAAS on Cassava Crop

Factors	**Accuracy** (Used MMRE)	**Time** (Used stopwatch)	**Cost** (Used ROI)	**Soil pH** (Used Digital soil Tester)	**Soil Texture** (Used Digital soil Tester)	**Crop Yield** (Used Yield Evaluation Metric)
Existing System	0.54	1800secs	50%	6.5	25mm	4.0tons/ha
IAAS	0.20	600secs	121.14%	6.0	12-25mm	7.0tons/ha

Analysis presented in Table 2 shows that the Intelligent Agronomic Advisory System (IAAS) surpasses previous methods used by smallholder farmers. The IAAS delivers a higher crop yield of 7.0 tons/ha and a Return on Investment (ROI) of 121.14%. It achieves a Mean Magnitude of Relative Error (MMRE) of 0.200 and requires less time due to its efficient coordination of farm processes. These results were obtained from field trials where smallholder farmers tested the newly developed system. The IAAS is cost-effective, easy to implement, and highly accurate, demonstrating superior performance compared to existing systems. The network training for the IAAS resulted in a minimal Mean Absolute Error (MAE) of approximately 5903, verifying its effectiveness in predicting crop yields in Nigeria.

5. Summary and Conclusion

5.1. Summary

The study developed an innovative system that integrates Artificial Neural Networks (ANN) with colored petri nets to boost crop productivity for smallholder farmers in Nigeria.

The colored petri nets managed the resources and timing needed for each farm task, coordinating processes such as site selection, tilling, planting, weeding, irrigation, fertilizing, and harvesting. The ANN predicts crop yields based on input variables like farm size, crop type, water needs, temperature, humidity, and soil conditions.

The implementation was carried out using Python in the PyCharm IDE, along with tools like the Petri Nets Simulator and MariaDB. The ANN was trained using climate data from NIMET and soil data from the College of Agronomy at the University of Agriculture, Makurdi, covering 60 years of climate records and soil samples from various locations around Makurdi. The training of the model resulted in a Mean Absolute Error (MAE) of approximately 5903, indicating only a slight deviation from the standard cassava yield value of 8.76 tons/ha and validating the model's effectiveness. Graphical results and system evaluations showed high accuracy and performance, confirming the model's reliability and usefulness in predicting crop yields for smallholder farmers in Nigeria.

5.2. Conclusion

The study developed an intelligent agronomic advisory system designed to forecast crop yields with a focus on benefiting smallholder farmers and agricultural stakeholders. By comparing current technologies with traditional manual methods, the research demonstrated that technological systems significantly surpass conventional methods in predicting crop yields. The research incorporated colored petri nets to model farm process workflows, proving effective through simulations that demonstrated liveness and reachability. Additionally, an Artificial Neural Network (ANN) model was established to predict crop yields, and a software application was created to offer yield predictions, improvement percentages, and advisory services to farmers. Performance evaluations of the system, measured against other methods, considered factors such as accuracy, cost, time, soil pH, and crop yield. The results indicated that the system outperformed existing methods, highlighting its effectiveness in improving crop yields and enhancing the livelihoods of farmers. The study emphasizes the potential societal benefits of adopting advanced technological solutions in agriculture. It supports policies that promote technology use in farming to maximize benefits for smallholder farmers and their communities.

Declarations

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