
An Integrated Feedforward Neural Network for Categorical Prediction of Greenhouse Tomato Yield under Nigeria's Climatic, Soil, and Agronomic Parameters

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Abstract

Accurate prediction of tomato yield in greenhouse environments is essential for sustainable agriculture, particularly under Nigeria's unique climatic, soil, and agronomic conditions. This study presents an integrated Feedforward Neural Network (FNN) model for the categorical prediction of greenhouse tomato yield, classified into low, medium, and high. The model integrates heterogeneous datasets encompassing climatic, soil, and agronomic features through a unified network architecture, data preprocessing, regularization, and cross-validation, which are employed to enhance generalization and predictive accuracy. The FNN, chosen for its simplicity and computational efficiency, achieved an overall accuracy of 93%, with strong precision, recall, and F1-scores across yield categories. These results highlight the potential of the proposed model for data-driven yield prediction and sustainable greenhouse management in Nigeria.

A. Introduction

The adoption of data-driven techniques is essential for enhancing agricultural productivity and sustainability [1]. However, effective implementation requires a comprehensive understanding of the farm landscape, the extent of technological adoption, and the prevailing challenges, including unpredictable climatic conditions, soil degradation, and inefficient farming practices, which collectively hinder crop yield, particularly for high-value crops such as tomatoes [2]. To address these challenges, greenhouse farming has emerged as a viable solution by providing a controlled environment that optimizes growing conditions and mitigates external uncertainties [3]. Greenhouse farming is a farming practice that offers a controlled environment that enhances crop productivity and optimizes resource utilization by reducing dependence on natural climatic conditions [4]. Moreover, it promotes sustainable agricultural practices by conserving water through precision irrigation and reducing land requirements compared to traditional open-field farming. These benefits position greenhouse cultivation as a vital approach to addressing global challenges related to food security, limited resources, and environmental sustainability.

In Nigeria, accurately predicting greenhouse tomato yields remains a major challenge due to the complex interactions among climatic factors, soil characteristics, and agronomic practices [5], as well as limitations in the predictive models used. Existing approaches often depend on historical climatic and soil data and utilize deep learning models that may struggle when data distribution shifts, resulting in poor generalization. Moreover, the complexity of these models often heightens the risk of overfitting, particularly when trained on noisy or limited datasets, which can result in suboptimal decision-making [6]. In such cases, the model tends to capture irrelevant or random patterns in the training data rather than the true underlying relationships. Consequently, it performs well on the training set but fails to generalize effectively to new or unseen data. This limitation leads to inaccurate yield predictions, unreliable decisions, and inefficient resource utilization in greenhouse management. Practically, this means that farmers and researchers may draw incorrect conclusions about yield performance under different conditions, thereby reducing the model's real-world applicability.

To address these limitations and improve predictive accuracy, this study adopts a Feed Forward Neural Network (FNN) for greenhouse tomato yield prediction. The FNN model is particularly suitable due to its ability to uncover hidden nonlinear relationships among variables influencing yield. Furthermore, it can integrate multisource data such as temperature, humidity, CO₂ concentration, irrigation patterns, soil pH, and nutrient levels, thereby supporting more accurate and data-driven decision-making for sustainable greenhouse operations [1]. In Nigeria, where smallholder farmers dominate the agricultural sector, adopting this method could enhance productivity and resilience against climate variability [7].

In this study, an FNN capable of providing accurate tomato yield predictions with three output categories (Low, Moderate, High), and offering more insights than existing binary classification methods is proposed. This scalable method efficiently processes diverse greenhouse data while maintaining computational efficiency, making it adaptable to various greenhouse environments. By bridging

the divide between machine learning [8] and practical farming needs, this research contributes to sustainable agricultural practices.

The remainder of this paper is organized as follows: Section B discussed the reviewed literature. Section C discusses the methodology. Section D presents the analysis of the proposed system. Section E presents the analysis of results and evaluation and Section F present the conclusion.

B. Related Works

Tomato production, as a globally significant horticultural crop, requires an efficient predictive modeling due to its sensitivity to environmental conditions and cultivation practices. Traditional yield estimation methods relied heavily on empirical observations, statistical correlations, and process-based crop models that often failed to capture the complex, nonlinear relationships between growth factors.

From the study conducted by [9], a stacked ensemble model that combined multiple algorithms to achieve robust predictions ($R^2 = 0.896$) while handling correlated input features was proposed. The system employed a two-phase approach with offline model training and online prediction that maintained computational efficiency. The model specifically addressed multicollinearity issues common in agricultural datasets through advanced feature selection techniques. Comparative analysis demonstrated superior performance to individual models like Random Forest and LightGBM, particularly in handling the complex interactions between greenhouse climate variables and crop parameters.

Similarly, [10] implemented a hybrid GA-LSTM model where genetic algorithms automatically tuned network hyperparameters. This approach achieved 93% prediction accuracy while reducing data requirements through transfer learning. The study utilized data from both indoor and outdoor tomato growing systems, analyzing variables including temperature, irrigation schedules, and soil quality. While computationally intensive during training, the optimized model showed significant improvement over standalone LSTM networks in prediction error reduction, particularly for high-yield scenarios.

In another study, [11] focused on integrating CNN-processed visual data with environmental sensor inputs, achieving 92% classification accuracy. The multimodal system combined hyperspectral imaging with microclimate data but faced limitations in resource requirements. The model demonstrated particular effectiveness in capturing spatial-temporal variability through advanced image processing techniques. However, the study noted challenges in generalizing the approach across different greenhouse architectures and tomato varieties without substantial retraining.

[12] developed a model to characterize and predict tomato yield under greenhouse conditions using temperature, relative humidity, soil moisture, and fruit count as key variables. An Artificial Neural Network (ANN) was trained to predict and optimize yield performance within a Model Predictive Control (MPC) framework. The study reported that integrating the MPC enhanced tomato production to 42.7 tons, compared to 35 tons achieved with the standalone ANN, indicating a significant improvement over the conventional neural network model.

Also, [13] applied artificial neural networks (ANNs) combined with sensitivity analysis to predict greenhouse tomato yield the most influential inputs were observed on tomato production. The models were created using data randomly collected by a face-to-face survey from 25 greenhouse tomato farms in Biskra Province, Algeria. Different ANN models were tested by varying the number of neurons in the hidden layer from 1 to 40. Based on the statistics criteria, the best structure found is 12–34–1. This ANN model was used to estimate tomato yield using the energy inputs. Then, the results of the ANN model were compared with those from the multiple linear regression (MLR) technique. The results illustrated that ANN provided more accurate predictions than the MLR technique. Sensitivity analysis also revealed that insecticides, farmyard manure (FYM), potassium (K₂O), nitrogen (N), electricity, and fungicides were the most significant inputs in the greenhouse tomato production.

Additionally, [14] proposed an automatic tomato yield predictor to assist human operators in anticipating weekly fluctuations. Environmental variables inside the greenhouse, namely, temperature, CO₂, vapour pressure deficit (VPD), and radiation, as well as past yield, were selected predictors. Greenhouse environment data and crop records from a large-scale commercial operation, Wight Salads Group (WSG) in the Isle of Wight, United Kingdom, collected from 2004 to 2008, were used to model tomato yield using an Intelligent System called “Evolving Fuzzy Neural Network” (EFuNN). Results from this study showed that the EFuNN model predicted weekly fluctuations of the yield with an average accuracy of 90%.

Study [15] explored the impact of climate variability on tomato yield in Nigeria, focusing on key climatic parameters such as temperature, rainfall, humidity, and solar radiation. The review synthesized findings from existing literature, case studies, and scientific reports to evaluate how these factors influence tomato growth, productivity, and vulnerability to pests and diseases. The study revealed that extreme temperature fluctuations adversely affect yield by disrupting flowering, fruit set, and overall plant physiology. Irregular rainfall patterns, ranging from droughts to excessive precipitation, were found to cause soil degradation, water stress, and heightened disease incidence. Similarly, high humidity levels favored the proliferation of fungal and bacterial pathogens, whereas low humidity accelerated water loss and reduced fruit quality. The review also discussed the socio-economic consequences of climate variability, including reduced farmer income, increased production costs, and heightened food insecurity due to adaptation challenges. However, the study did not address greenhouse-based tomato yield prediction.

Finally, [16] investigated tomato yield, crop water use, and water productivity of field-grown, drip-irrigated tomatoes under regulated deficit irrigation conditions in Afaka, Nigeria. The study further simulated various deficit and irrigation method scenarios using the AquaCrop model (version 6.0). Model inputs included weather data, crop parameters, irrigation schedules, field management practices, soil and groundwater characteristics, planting or transplanting dates, and initial simulation conditions. The research primarily focused on agronomic factors, particularly irrigation methods (drip, basin, and

furrow) and fruit dry yield, to predict tomato yield in open-field conditions rather than in a greenhouse environment.

While numerous studies have explored tomato yield prediction using diverse machine learning and deep learning techniques, none have specifically implemented a Feedforward Neural Network (FNN) model for greenhouse tomato yield prediction under Nigerian climatic and agronomic conditions, thereby establishing the novelty of this research.

C. Research Method

The methodology for this study was carefully designed to develop a neural network-based predictive model for greenhouse tomato yields. The research followed a systematic approach encompassing data collection, preprocessing, model development, and evaluation to ensure reliable and practical results. The study utilized a comprehensive dataset from the various Greenhouses in Nigeria, which included detailed measurements of environmental conditions, crop parameters, and soil properties across multiple tomato growth cycles and agronomic factors. The dataset consisted key features such as temperature ranging between 21-30°C, humidity levels from 51-100%, CO₂ concentrations between 472-540 ppm, drain pH at 6.5, electrical conductivity of 0.3 ds/m, and various plant morphological characteristics including stem thickness measurements between 7.1-12.8 mm to ensure data quality and consistency. The data was sourced from greenhouse farms in Akwa Ibom State, Nigeria and preprocessed for used in this study. The preprocessing steps include, one-hot encoding to handle categorical data, data normalization using min-max model, and features selection using L1 regularization method.

Table 1. Dataset Description

Features of dataset	Feature name
Temperature in greenhouse	temperature
Humidity in greenhouse	humidity
CO ₂ in greenhouse	CO ₂ _air
CO ₂ dosing	CO ₂ _dosing
Drain pH	drain_pH
Drain EC	drain_EC
Cumulative irrigation	cumm_irrigation
Stem thickness	stem_thick
Stem growth	stem_growth
Stem density	stem_density
Plant density	plant_density
Total inside PAR (sun +HPS +LED)	total_par
Tomato yield	tomato_yield

1. Proposed Architecture

The proposed system for predicting tomato crop yield in greenhouse environments in Figure 1 utilizes feed forward neural network to address the challenges of controlled agricultural production. This system integrates

greenhouse environmental data, soil, climatic and agronomic factors, processes it through neural network model and identifies key variables influencing crop productivity. The proposed feed forward neural network system provides accurate tomato yield predictions with three output categories (Low, Moderate, High), offering more insights than binary classification methods.

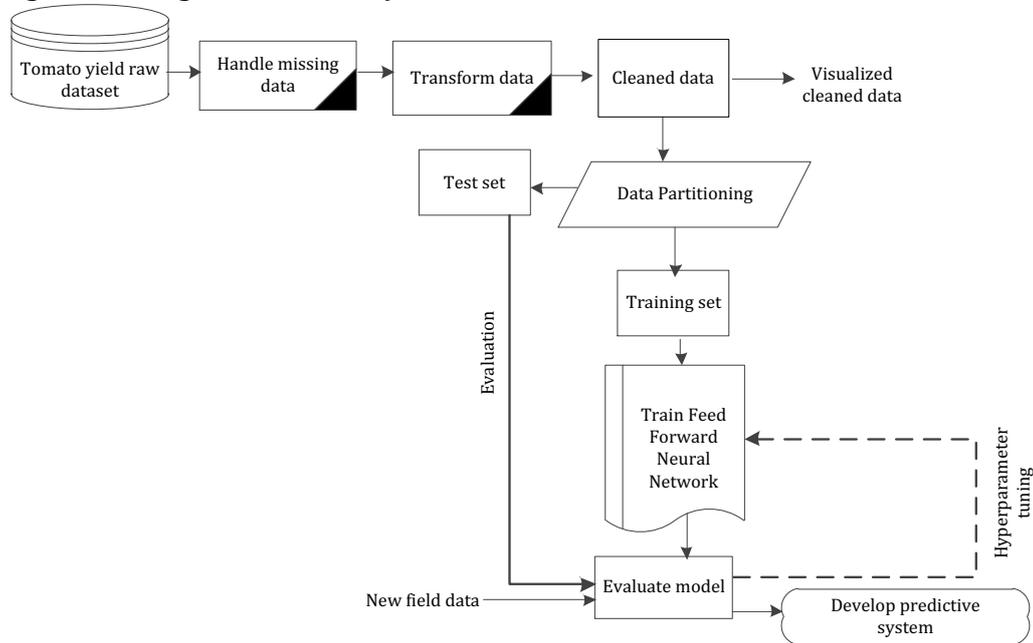


Figure 1. Architecture of the proposed system

2. Correlation of features of tomatoes crop yield

The matrix in Figure 2 helps identify key relationships between features, which can be useful for predictive modeling and feature selection in data analysis. Generally, a correlation coefficient of 0.80 and above is regarded as a strong correlation while the values between 0.34 and 0.79 are often regarded as moderate correlation. Between the values between 0.00 to 0.33 signifies a low correlation [17]. In this study, features ranging from 0.30 to 0.67 are considered relevant features without dependency. However, a correlation coefficient ranging from 0.80-1.00 is considered a highly dependent feature, and one such feature is discarded to minimize bias in the predictive model.

Each cell in the matrix represents the correlation coefficient between two features, ranging from -1 (strong negative correlation) to 1 (strong positive correlation). The color gradient from blue to red visually indicates the strength of the correlation, with red representing higher positive correlations and blue representing negative or weak correlations. For example, "humidity" has a strong negative correlation with "pH_drain" (-0.63), meaning that as humidity increases, pH levels in the drain tend to decrease. On the other hand, "temperature" and "total_PAR" (photosynthetically active radiation) show a strong positive correlation (0.67), suggesting that higher temperatures are associated with increased PAR levels. The "yield_status" variable, which likely represents crop yield, has relatively weak correlations with most features, implying that multiple factors may influence it rather than a single dominant variable.

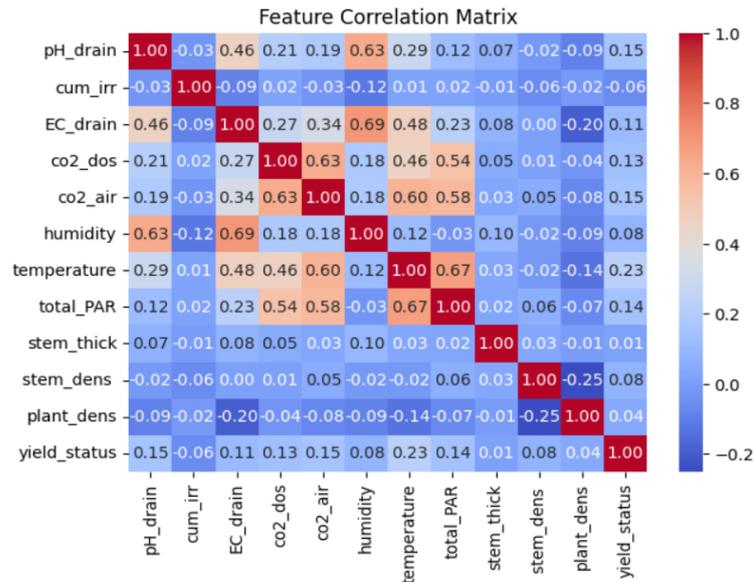


Figure 2. Feature correlation matrix analysis

3. Model Development

The feedforward neural network structure included an input layer with 12 nodes corresponding to the selected features, followed by two hidden layers with 64 and 32 neurons respectively, both utilizing ReLU activation functions. The output layer consisted of 3 neurons with SoftMax activation, representing the low, moderate, and high yield classifications. To enhance model generalization and prevent overfitting, the architecture incorporated L2 regularization with a lambda value of 0.01 and dropout layers with a rate of 0.2. This architecture was implemented using the TensorFlow/Keras framework with training conducted on Google Colab utilizing a Tesla T4 GPU with 16GB RAM to handle the computational demands of the model.

Likewise, model training and optimization were conducted with careful attention to achieve optimal performance while avoiding overfitting. The Adam optimizer was employed during the training of the dataset with a learning rate of 0.01 and beta values of 0.9 and 0.999, providing efficient gradient descent with momentum. Categorical cross-entropy served as the loss function, appropriate for the multi-class classification task. Training proceeded with a batch size of 32 across 100 epochs, incorporating early stopping with a patience of 10 epochs to prevent unnecessary computation. The dataset was split into 80% training set for training and 20% for testing, with 5-fold cross-validation applied during training to ensure model robustness across different data subsets.

4. Analysis of result

i. Density Distribution of pH, Irrigation, and EC Drain by Yield Status

In Figure 3, this set of density plots illustrates the distribution of three variables (pH_drain, cum_irr, and EC_drain) based on different yield statuses (0, 1, and 2). Each plot represents how these variables vary across the yield status categories, with different shades distinguishing between them. The pH levels of the

drain water exhibit multiple peaks across all yield statuses. Higher yield categories (status 2) tend to have a stronger concentration around 7.0 to 7.5, whereas lower yield categories (status 0) are more spread out across lower pH values. Furthermore, cumulative irrigation shows a sharp peak near 0 across all yield statuses, with a small distribution extending towards higher values. This indicates that most observations have low irrigation values, but some cases receive more irrigation, especially in status 2. The electrical conductivity of the drain water displays distinct peaks, particularly around 4 to 6, where most of the observations are concentrated. The distribution appears consistent across yield statuses, but higher yield categories (status 2) slightly dominate the primary peak.

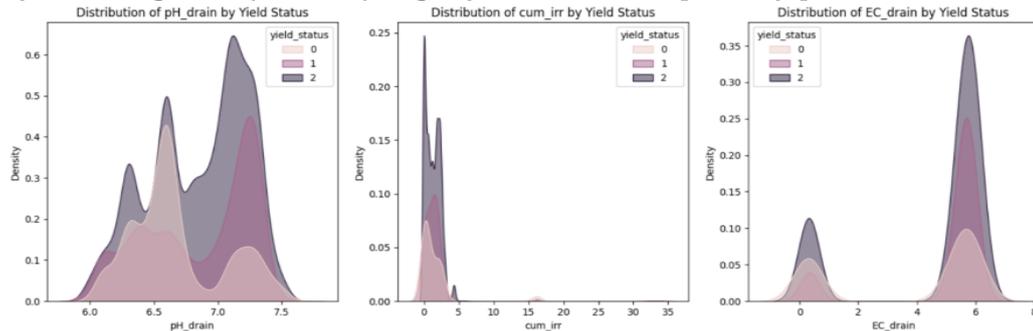


Figure 3. Density Distribution of pH, Irrigation, and EC Drain by Yield Status

ii. Density Distribution of CO₂, Humidity, and Temperature by Yield Status

The set of density plots in Figure 4 visualizes the distribution of CO₂ levels in the air, humidity, and temperature across different yield statuses (0, 1, and 2). Each curve represents how these environmental factors vary for different yield categories. The CO₂ concentration shows multiple peaks, with most observations between 500 and 1,500 ppm. Higher yield status (2) appears to have stronger concentrations around 750 and 1,250 ppm, suggesting an optimal CO₂ range for better yield. In the case of humidity, it is widely distributed, with most data points between 60% and 100%. Higher yield (status 2) is more concentrated at 90% to 100%, indicating that increased humidity levels might be favorable for better yield. While the temperature distribution reveals peaks around 18°C and 25°C, with higher yield (status 2) being more prominent at the upper temperature range. This suggests that moderate to slightly higher temperatures might be beneficial for improved yield outcomes. Nevertheless, plots highlighting how variations in CO₂, humidity, and temperature correspond to different yield statuses, providing insights into the environmental conditions that may influence crop performance.

D. Result and Discussion

Confusion matrix in Figure 5 shows the level of predictions and how they hold up against the actual values. Heatmap of the confusion matrix illustrates the performance of a feedforward neural network in classifying three categories. The rows represent actual (true) labels, while the columns represent predicted labels. The model correctly classified 633 instances of class 0, 748 instances of class 1, and 1,537 instances of class 2, as indicated by the diagonal values. 15 instances were misclassified as class 1, and 32 as class 2, showing low yield while in

Moderate yield, 30 instances were misclassified as class 0, and 78 as class 2 and High yield (class 2) having 27 instances misclassified as class 0, and 38 as class 1. The color intensity represents the frequency of classifications, with darker shades indicating higher values. Overall, the model performs well, particularly for class 2, but has some misclassification in classes 0 and 1, suggesting potential room for improvement in distinguishing between these categories. Analysis of the confusion matrix indicated minimal misclassification between extreme classes (low vs high), with the majority of errors occurring between adjacent classes (low-moderate and moderate-high), suggesting the model effectively captured the underlying patterns distinguishing yield categories.

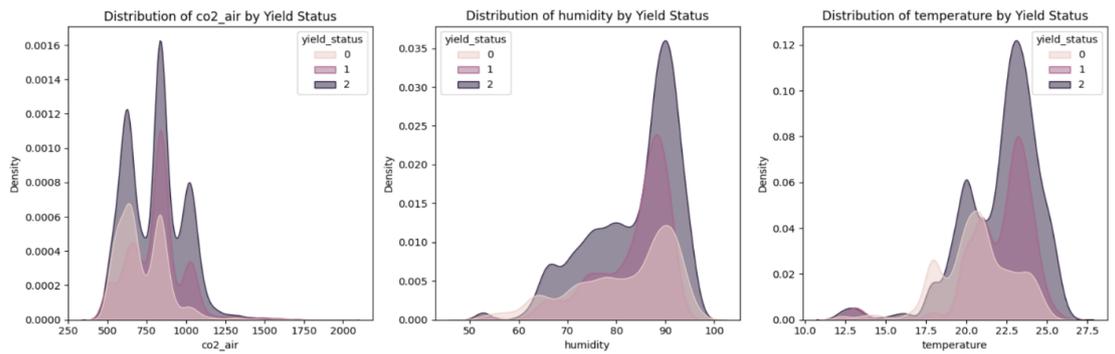


Figure 4. Density Distribution of CO₂, Humidity, and Temperature by Yield Status

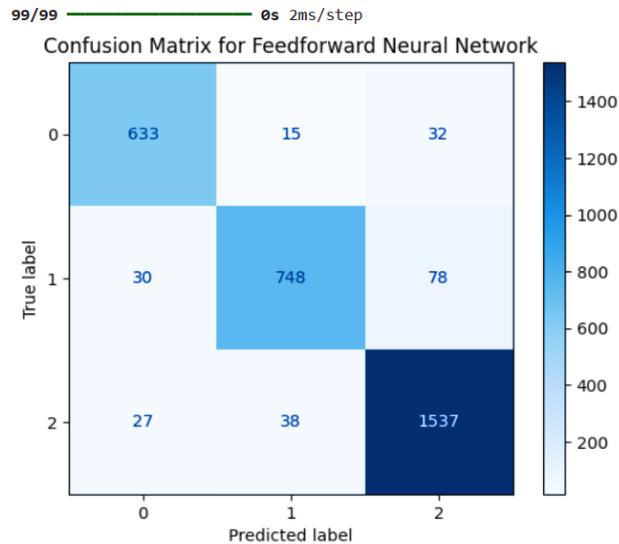


Figure 5. Confusion Matrix for Feedforward neural network

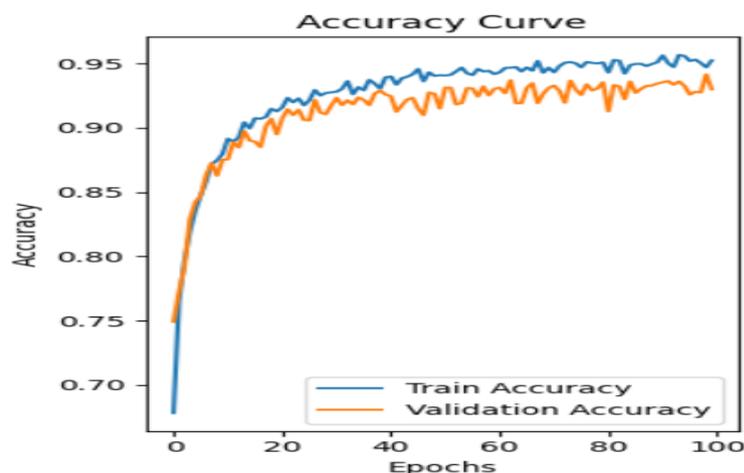
However, the model performance as presented in Table 2 achieved an overall accuracy of 93%, with class-specific metrics revealing strong performance across all yield categories. For low yield prediction, precision reached 98.1% with recall of 93.4% and F1-score of 95.7%. Moderate yield prediction showed slightly lower but still robust performance with 97.2% precision, 86.8% recall, and 90.1% F1-score. High yield prediction demonstrated exceptional performance with 99.4% precision, 96.0% recall, and 97.7% F1-score.

Table 2. Result evaluation with relevant metric

Class	F1-Score	Precision	Recall
Low	0.9217	0.9814	0.9338
Moderate	0.9013	0.9723	0.8679
High	0.9517	0.9943	0.9603

1. Accuracy Curve

The graph in Figure 6 represents the accuracy curve of FNN model over 100 epochs, comparing training and validation accuracy. The blue line indicates training accuracy, while the orange line represents validation accuracy. Initially, both accuracies increase rapidly, signifying that the model is learning effectively. Around epoch 50, the training accuracy surpasses 90% and continues improving steadily, reaching about 95% by the final epoch. The validation accuracy also increases but fluctuates more, stabilizing around 92%. The result of the experiment showed that FNN Algorithm performed well in prediction with the accuracy of 93% and is used for the development of the prototype system.

**Figure 6.** Accuracy curve

2. Discussion of findings

The Feedforward Neural Network (FNN) was employed to assess both training and validation accuracy, as illustrated in the accuracy curve figures. The model exhibited superior robustness and performance, attributed to its flexibility and capacity to capture complex non-linear relationships often present in greenhouse environments. The high accuracy achieved underscores the model's exceptional effectiveness in predicting tomato yields. A key factor contributing to this effectiveness was the model's ability to efficiently train and integrate both small numerical datasets and categorical variables, enabling a more comprehensive analysis of factors influencing tomato yield. This extensive training process produced reliable experimental results, demonstrating that the

Feedforward Neural Network performs well on small datasets with non-linear interactions, effectively mitigating overfitting issues in yield prediction.

3. System Implementation

Finally, a prototype system was developed, integrating a Python Flask API as the backend to host and serve the trained model, while the frontend was built using Streamlit to provide an intuitive and user-friendly interface. The system was optimized on a configuration featuring 8GB of RAM and a 4-core CPU to ensure efficient model performance. This setup enabled the creation of a robust, accurate, and practical predictive platform for estimating greenhouse tomato yields.

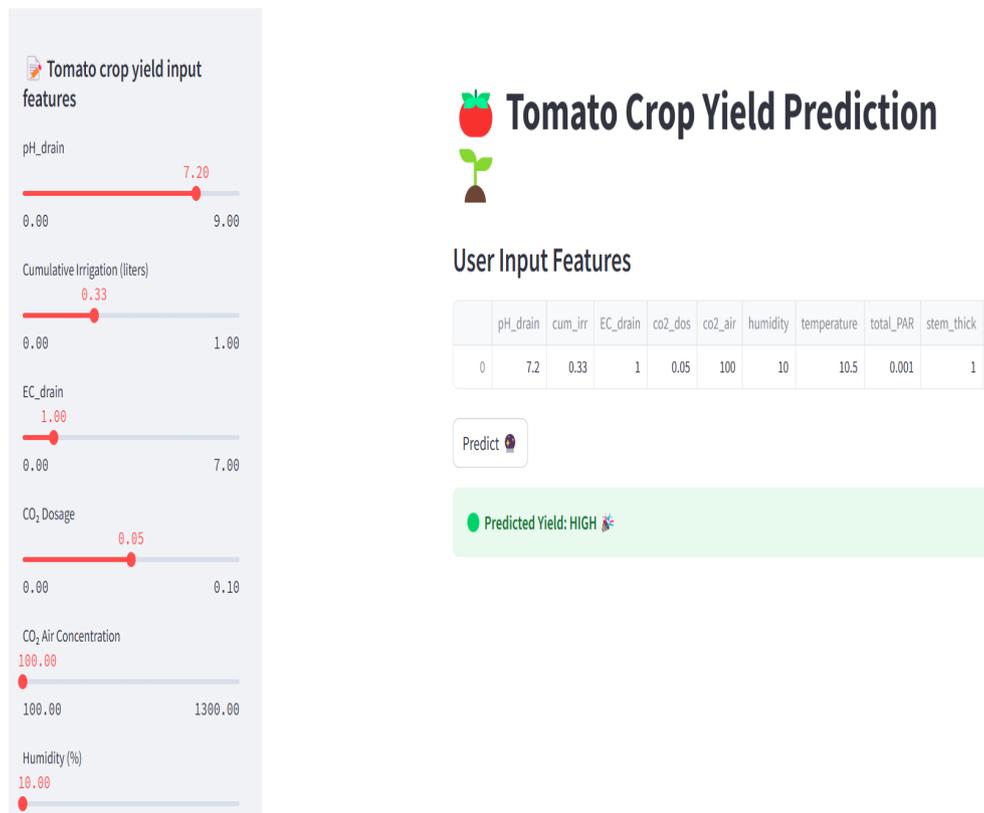


Figure 7. Prototyped of the Implemented System

E. Conclusion

In conclusion, this research successfully developed a FNN model to predict tomato crop yields in greenhouse environments. By leveraging data on greenhouse climate, crop parameters and soil factors, the study has demonstrated the potential of machine learning to provide accurate and reliable yield forecasts. The model’s performance underscores the importance of integrating advanced computational techniques into agricultural practices to enhance efficiency and production.

F. Competing Interest

The authors declare that they have no known financial or personal relationships that could have influenced the work reported in this paper.

G. Funding

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H. Conflict of Interest

The authors declared that there are no conflicts of interest regarding the publication of this work.

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