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AI-Based Vegetable and Fruit Advisory with Disease Detection, and Farm Resource Allocation Framework

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***Abstract:** Agriculture plays a key role in ensuring food security and economic growth. However, farmers often struggle with choosing the right crops, predicting yield, managing resources, and spotting plant diseases. Traditional farming depends on manual decision-making and limited data analysis. This can result in lower productivity and wasted resources. To solve these problems, this paper proposes an artificial intelligence (AI)-based advisory system for fruits and vegetables. This system combines crop recommendations, yield predictions, disease detection, and resource management. The proposed system uses agricultural factors like soil nutrients (NPK values, pH), temperature, rainfall, humidity, and past crop data. A fuzzified recurrent neural network (FRNN) is used for crop recommendations since it manages uncertainty and time patterns in agricultural data effectively. The model examines input conditions and suggests the best crops for farming. Additionally, regression methods are used for yield prediction to estimate expected production. To assist farmers during the growing phase, the system includes an image-based module for disease detection. Plant images are prepared using techniques like resizing, noise reduction, and contrast improvement for better quality. A convolutional neural network (CNN) then accurately identifies plant diseases and provides treatment suggestions, including fertilizers and preventive actions.*

Moreover, the system recommends the best way to allocate resources like water, fertilizers, and land to enhance efficiency and sustainability. A user-friendly web interface created with Flask allows farmers to easily engage with the system and access recommendations. The proposed framework supports data-driven decision-making at every stage of the crop lifecycle. This helps increase productivity, reduce losses, and foster sustainable farming practices.

***Keywords:** Artificial Intelligence, Fuzzified Recurrent Neural Network (FRNN), Crop Recommendation, Yield Prediction, Disease Detection, Convolutional Neural Network (CNN), Image Processing, Agriculture.*

I. INTRODUCTION

Agriculture is crucial for global food production and economic growth, especially in developing countries where it supports many livelihoods. However, modern agriculture faces major challenges with crop selection, resource management, and productivity due to the changing and uncertain environmental and soil conditions. Factors like soil nutrients, temperature, humidity, and rainfall change constantly. This makes it tough to make agricultural decisions, which can be complex and non-linear. Traditional farming relies on manual knowledge and fixed analysis. These methods often miss these variations, leading to poor crop choices and inefficient resource use [1].

With the rise of Artificial Intelligence (AI), data-driven methods have become more popular in agriculture. Machine learning and deep learning models can analyze large amounts of agricultural data and find complex patterns that typical methods don't easily reveal [2]. However, raw agricultural data often has inconsistencies and needs preprocessing to work well with models. For this reason, techniques like Min-Max normalization are used to adjust input features to a consistent range. This helps ensure stability and efficiency during training [3].

Neural network-based methods have had good results in modeling agricultural data. Specifically, Recurrent Neural Networks (RNNs) are good at capturing relationships among environmental factors. Activation functions like Rectified Linear Unit (ReLU) help introduce non-linearity for learning complex patterns [4]. During training, Backpropagation computes gradients, and optimization methods like Mini-Batch Stochastic Gradient Descent (SGD) efficiently update model weights. Despite these improvements, many traditional models do not handle the uncertainty found in real-world agricultural data [5].

To address these issues, this work presents a Fuzzified Recurrent Neural Network (FRNN), which combines fuzzy logic with RNN. In this method, input features use a Gaussian membership function to effectively represent uncertainty and imprecision. The RNN part then learns the time-related and non-linear connections among features, leading to better crop recommendations and resource allocation [6].

Besides crop recommendations, disease detection is also important in modern agriculture since plant diseases can greatly affect yield and quality. Checking plant leaves manually takes a lot of time and can lead to human errors. To solve this, the proposed system includes an image-based disease detection module. It first applies image preprocessing techniques like resizing, Gaussian noise reduction, and contrast enhancement to improve image quality. A Convolutional Neural Network (CNN) is then used to automatically extract features and accurately identify plant diseases [7].

Additionally, the proposed system is set up as a full-stack web application to ensure user-friendliness and scalability. The frontend uses React.js with Vite, Tailwind CSS, and Axios, while the backend is built with Node.js and Express.js to provide RESTful services [8]. This integrated framework combines preprocessing algorithms, FRNN-based learning, and CNN-based image processing. It offers an efficient and smart solution for crop recommendations, resource management, and disease handling, which improves agricultural productivity and sustainability [9].

The main contributions of this work include:

1) To manage uncertainty and increase the accuracy of crop recommendations, a Fuzzified Recurrent Neural Network (FRNN) is suggested.
2) The model incorporates training and preprocessing methods such as Mini-Batch SGD, ReLU activation, Min-Max normalization, and Backpropagation.
3) To offer several appropriate options for decision-making, a Top-3 crop recommendation strategy is presented.
4) For precise classification, an image-based disease detection module that uses CNN and image processing techniques is integrated.
5) React.js and Node.js are used in an full-stack web implementation to create an end-to-end agriculture system.

II. LITERATURE REVIEW

Agriculture resource on Crop recommendation and disease detection using Artificial Intelligence have become very important in years. This is because we need agriculture solutions. When farmers make decisions, they have to think about things that are not certain like the soil nutrients, the weather and the environment. The old ways of farming rely on what people know and do not change much which is often not good enough and not accurate. To make things better researchers have suggested using machine learning and learning-based systems to predict crops estimate yields and detect diseases.

Kamilaris and Prenafeta-Boldú [1] presented a comprehensive survey on deep learning applications in agriculture, emphasizing the effectiveness of Convolutional Neural Networks (CNNs) for plant disease detection and classification. Similarly, Mohanty et al. [2] demonstrated that CNN-based models can achieve high accuracy in identifying plant diseases from leaf images. However, these approaches primarily focus on image-based analysis and do not incorporate environmental factors for decision-making.

Jeong et al. [3] proposed a machine learning-based crop recommendation system using environmental and soil data. Their model utilized classification algorithms such as Random Forest and Support Vector Machines (SVM). Although the system provided reasonable accuracy, it lacked the ability to model temporal dependencies and handle uncertainty in agricultural inputs. To address uncertainty, fuzzy logic-based systems have been explored. Zadeh’s fuzzy logic theory [4] has been widely applied in agriculture for handling imprecise data. For instance, Patel et al. [5] developed a fuzzy-based crop recommendation system, which improved decision-making under uncertain conditions but lacked learning capability for complex patterns.

A. FRNN-Based Crop Recommendation Models.

Fuzzified Recurrent Neural Networks (FRNN) combine logic and Recurrent Neural Networks (RNN) to handle uncertainty and things that happen over time. In this approach the input features are changed using a membership function:

f(x) = e^(-(x. 0.5)^2 / 0.1)

Where x is the value of the input feature.

The RNN part looks at data that happens in a sequence. Finds relationships between things like the environment. The hidden layer uses the ReLU activation function:

ReLU(x) = max(0, x)

The output layer uses Softmax activation to make probability distributions:

$\text{Softmax}(y_i) = e^{y_i} / \Sigma e^{y_j}$

This hybrid approach makes crop recommendation more accurate by handling both uncertainty and non-linear relationships.

B. Image Processing and CNN-Based Disease Detection.

People have been studying how to detect plant diseases using pictures and deep learning. Krizhevsky and his team showed that Convolutional Neural Networks are really good at looking at pictures and figuring out what is in them. In farming these networks can look at pictures of leaves. Find diseases by looking at things like texture and colour.

The way Convolutional Neural Networks work can be represented by an equation:

$F (x, y) = \Sigma I(i, j) * K (x. I, y. J)$

where I's the picture K is a special filter and F (x, y) is the result.

Before putting pictures into the Network they are cleaned up. Made better. This helps the network to work accurately. Crop recommendation and disease detection using Artificial Intelligence are important for plant disease detection.

C. Training Algorithms in Neural Networks

To train networks we need special algorithms and functions. One common algorithm is called Mini-Batch Stochastic Gradient Descent. The way it updates the weights is:

$W = W. H \nabla W$

Where:

η's the learning rate and ∇W is the gradient of the loss function.

The loss function used for classification is:

$L = -\Sigma \text{ y\_true} \log(\text{y\_pred})$

The network is trained by looking at the data finding the gradients and updating the weights This happens times, which makes the network more accurate. Crop recommendation and disease detection using Artificial Intelligence require training algorithms.

D. Limitations of Existing Methodss

Although many deep learning models have been developed for lung cancer detection, several limitations still exist. CT scan images may contain noise, which affects feature extraction and reduces detection accuracy. In addition, CNN-based models often generate redundant features that increase computational complexity.

The common limitations of existing methods are summarized in Table.

Method Type	Description	Limitation
Traditional ML Models	Use statistical and rule-based approaches	Poor handling of non-linearity and uncertainty
Fuzzy-Based Models	Use statistical and rule-based approaches	Lack learning capability
CNN-Based Models	High accuracy in image classification	Limited to image data only
RNN-Based Models	Capture temporal relationships	Cannot handle uncertainty effectively
Hybrid Models	Combine multiple techniques	High complexity and computational cost

From the analysis, it is evident that existing methods either focus on uncertainty handling or pattern learning, but not both simultaneously. Moreover, most systems lack integration of crop recommendation, resource allocation, and disease detection in a single framework. These limitations motivate the proposed FRNN-based system, which combines fuzzy logic, RNN, and CNN into a unified architecture for efficient and intelligent agricultural decision-making.

III. PROPOSED SYSTEM

The proposed system introduces an intelligent AI-based agricultural advisory framework that integrates crop recommendation, resource allocation, and plant disease detection. The primary goal of this system is to enhance agricultural decision-making by combining environmental data analysis with image-based disease identification. By leveraging advanced machine learning and deep learning techniques, the system supports farmers in both pre-cultivation and post-cultivation stages.

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Initially, the system collects soil and environmental parameters such as nitrogen (N), phosphorus (P), potassium (K), pH level, temperature, humidity, and rainfall. These parameters play a crucial role in determining crop suitability. However, real-world agricultural data often contains inconsistencies, variations, and uncertainties, which may reduce prediction accuracy. To address this issue, preprocessing techniques such as Min-Max normalization are applied to scale the input data into a uniform range, ensuring stability during model training.

Following preprocessing, the normalized data is transformed using a Gaussian membership function. This fuzzification process helps in handling uncertainty and imprecision present in agricultural data. The fuzzified inputs are then passed into a Fuzzified Recurrent Neural Network (FRNN), where the Recurrent Neural Network (RNN) captures complex relationships among environmental features. The hidden layer utilizes the Rectified Linear Unit (ReLU) activation function to introduce non-linearity, while the model is trained using Backpropagation along with Mini-Batch Stochastic Gradient Descent (SGD) for efficient optimization. The output layer applies the Softmax function to generate probability scores for different crops, and the system provides Top-3 crop recommendations to assist farmers in making informed decisions.

In addition to crop recommendation, the system incorporates a plant disease detection module based on image processing. Plant leaf images are preprocessed using resizing, Gaussian noise reduction, and contrast enhancement to improve image quality. A Convolutional Neural Network (CNN) is then employed to extract meaningful features and accurately classify plant diseases. By combining both data-driven and image-based analysis, the proposed system delivers a comprehensive agricultural solution that improves productivity and reduces risks.

A. System Overview

The proposed system integrates multiple intelligent modules to provide a unified agricultural advisory solution. Initially, environmental data is collected and preprocessed using Min-Max normalization to ensure consistency across all input features. The normalized data is then fuzzified using a Gaussian membership function, enabling the system to effectively handle uncertainty.

The processed data is fed into the FRNN model, which generates crop recommendations based on learned patterns. At the same time, plant leaf images are input into the disease detection module. These images undergo preprocessing techniques such as resizing and noise reduction, after which a CNN model extracts features and performs classification.

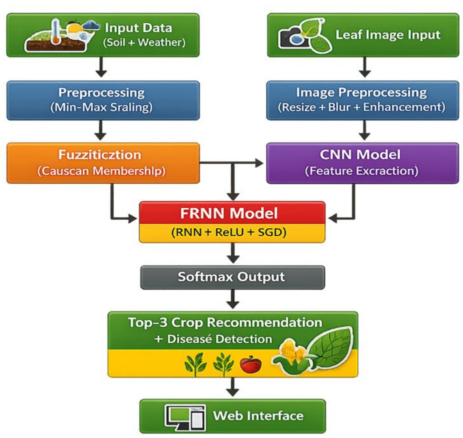


Fig.1.System Architecture of the Proposed Agricultural Advisory System.

B. System Architecture

The system architecture is designed as a multi-stage pipeline that efficiently processes both numerical agricultural data and image-based inputs. Initially, environmental parameters are collected and normalized using the **Min-Max Scaling algorithm**, which ensures that all input features are brought into a consistent range. This normalization step is essential for maintaining stability during training and improving the convergence of the learning model.

Following normalization, the system applies a fuzzification process using the Gaussian Membership Function algorithm:

$$f(x) = e^{-\frac{(x-0.5)^2}{0.1}}$$

This transformation allows the model to effectively handle uncertainty and imprecision inherent in real-world agricultural data. By converting crisp numerical inputs into fuzzy representations, the system becomes more capable of adapting to variations in environmental conditions.

The fuzzified data is then forwarded to the FRNN model, where the Recurrent Neural Network (RNN) algorithm is utilized to capture complex and non-linear relationships among the input parameters. Since agricultural factors often exhibit interdependencies, the sequential learning capability of RNN plays a significant role in improving prediction accuracy. Within this model, the hidden layer employs the ReLU activation algorithm, defined as:

$$\text{ReLU}(x) = \max(0,x)$$

The use of ReLU enhances computational efficiency and mitigates issues such as vanishing gradients, enabling the network to learn deeper representations.

At the output stage, the system applies the Softmax classification algorithm:

$$Softmax(y_i) = \frac{e^{y_i}}{\sum e^{y_j}}$$

This function converts the network outputs into probability distributions, allowing the system to rank crops and generate Top-3 recommendations based on their likelihood scores.

To optimize model performance, the training process is carried out using the Backpropagation algorithm in conjunction with the Mini-Batch Stochastic Gradient Descent (SGD) algorithm. Backpropagation enables efficient computation of gradients, while Mini-Batch SGD updates model parameters iteratively using subsets of data, ensuring faster convergence and improved generalization.

In parallel, the image-based disease detection module employs the Convolutional Neural Network (CNN) algorithm, which is widely used for image classification tasks. The CNN utilizes the 2D Convolution algorithm to extract spatial features such as texture, color, and patterns from plant leaf images. This enables accurate identification of plant diseases even under varying image conditions.

Overall, the integration of multiple algorithms—including Min-Max Scaling, Gaussian Membership Function, RNN, ReLU Activation, Softmax Classification, Backpropagation, Mini-Batch SGD, and CNN—forms a robust and intelligent framework. This combination enhances the system's ability to deliver accurate crop recommendations and reliable disease detection, thereby supporting effective and data-driven agricultural decision-making.

C. Data Preprocessing

Data preprocessing is a crucial stage in the proposed system, as agricultural datasets often contain noise, missing values, and inconsistencies that can negatively impact model performance. To address these challenges, the system employs the Min-Max Normalization algorithm, which scales the input features into a uniform range:

$$X' = X - Xmin \,/\, Xmax - Xmin$$

This normalization technique ensures that all input values lie within the range [0,1], thereby improving numerical stability and accelerating the convergence of the learning algorithms.

In addition to normalization, the system also incorporates the Missing Value Handling algorithm and Outlier Detection algorithm to improve data quality. These algorithms help in identifying and correcting incomplete or abnormal data points, ensuring that the model is trained on reliable and consistent information.

For image data, preprocessing is performed using a sequence of well-defined algorithms to enhance image quality before feature extraction. Initially, the Image Resizing algorithm is applied to convert all input images into a fixed dimension, ensuring compatibility with the CNN architecture. This is followed by the Gaussian Blur algorithm, which reduces noise and smooths the image by minimizing high-frequency variations.

To further improve the visibility of important features, the system utilizes the Histogram Equalization algorithm for contrast enhancement. This technique redistributes pixel intensity values, making patterns such as leaf spots, discoloration, and texture variations more distinguishable.

Additionally, the Image Normalization algorithm is applied to scale pixel intensity values, ensuring consistency across different images. In some cases, the Data Augmentation algorithm may also be used to increase the diversity of the training dataset by applying transformations such as rotation, flipping, and scaling, which helps in improving the robustness of the CNN model.

Overall, the integration of preprocessing techniques—including Min-Max Normalization, Missing Value Handling, Outlier Detection, Image Resizing, Gaussian Blur, Histogram Equalization, Image Normalization, and Data Augmentation algorithms—significantly enhances data quality. This results in improved feature extraction, higher model accuracy, and more reliable disease detection outcomes.

D. FRNN-Based Crop Recommendation

The crop recommendation module in the proposed system is based on the integration of fuzzy logic and deep learning through the Fuzzified Recurrent Neural Network (FRNN). This hybrid approach combines the uncertainty-handling capability of fuzzy systems with the sequence learning strength of neural networks.

Initially, the pre-processed input data is transformed using the Gaussian Membership Function algorithm, which converts crisp environmental parameters into fuzzy values. This allows the model to better represent real-world agricultural uncertainty. The membership function is defined as:

$$f(x)=e-2\sigma 2(x-\mu)2$$

where, μ represents the mean and σ represents the standard deviation.

The fuzzified inputs are then processed using the Recurrent Neural Network (RNN) algorithm, which captures complex dependencies among soil and weather parameters. Since agricultural data often exhibits interrelated patterns, the RNN effectively models these relationships over multiple input features.

Within the hidden layers, the system applies the ReLU Activation algorithm:

$$\mathrm{ReLU}(x) = \max(0,x)$$

This activation function introduces non-linearity and improves computational efficiency by eliminating negative activations.

At the output stage, the system utilizes the Softmax Classification algorithm to generate probability scores for each crop:

$$\mathrm{Softmax}(yi)=\sum jeyj/eyi$$

Based on these probabilities, the system selects the Top-3 crops with the highest scores, providing flexible and practical recommendations for farmers.

The training process is performed using the Backpropagation algorithm along with the Mini-Batch Stochastic Gradient Descent (SGD) algorithm, which iteratively updates the model weights to minimize prediction error. This combination ensures faster convergence and improved generalization performance.

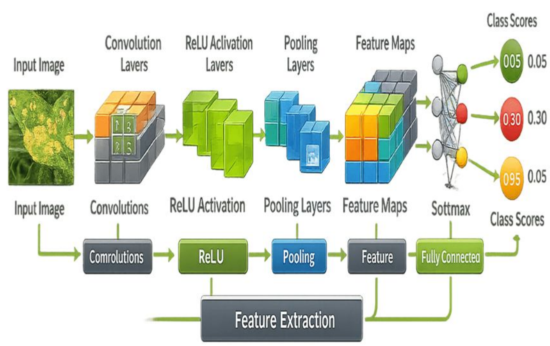


Fig 2. Feature Extraction process using CNN for plant Disease Detection.

E. CNN-Based Disease Detection

The plant disease detection module is designed using a deep learning approach based on the Convolutional Neural Network (CNN) algorithm, which is highly effective for image classification tasks. Initially, preprocessed plant leaf images are provided as input to the CNN model.

The network applies the 2D Convolution algorithm to extract spatial features from the images:

$$F(x,y)=i\sum j\sum I(i,j)\cdot K(x-i,y-j)$$

Where, I(i, j) reprasents the input image and K represents the convolution kernel.

The extracted feature maps are then passed through the Pooling algorithm, typically Max Pooling, which reduces the spatial dimensions and retains the most significant features:

$$P(x,y)=\max(Iregion)$$

This step helps in reducing computational complexity while preserving important patterns. To introduce non-linearity, the ReLU Activation algorithm is applied after each convolutional layer. The network may also include the Dropout Regularization algorithm, which randomly deactivates neurons during training to prevent overfitting and improve model generalization. Finally, the extracted features are flattened and passed to fully connected layers, where the Softmax Classification algorithm is used to predict the disease category:

$$Softmax(yi)=\sum eyj/eyi$$

This enables the system to classify plant diseases accurately based on visual patterns such as color variations, texture changes, and lesion formations. As a result, this module provides accurate disease classification, allowing early detection and timely intervention, which helps in minimizing crop loss and improving overall yield.

F. Cross-Entropy Loss Algorithm in using the both ML (FRNN) and DL

The performance of the proposed system is further enhanced by incorporating the Cross-Entropy Loss algorithm, which plays a crucial role in optimizing the classification accuracy of both the crop recommendation and disease detection modules. This algorithm is widely used in multi-class classification problems, as it effectively measures the difference between predicted probabilities and actual class labels.

In the proposed framework, the Cross-Entropy Loss algorithm is applied after the Softmax classification layer. The Softmax function converts the output of the model into a probability distribution, and the Cross-Entropy Loss evaluates how close these predicted probabilities are to the true labels. The loss function is defined as:

$$L=-i\sum yi\log(y\^{}i)$$

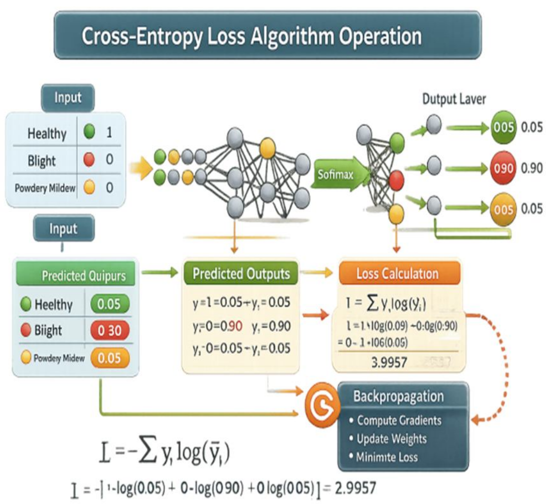


Fig. 3. Cross-Entropy Loss Computation and Backpropagation Process in the Proposed Agricultural Advisory System

G. Classification and Prediction output

The classification and output module is responsible for generating the final predictions based on the processed data from both the crop recommendation and disease detection modules. For crop recommendation, the system relies on the Softmax Classification algorithm to produce probability distributions over multiple crop classes. The crops with the highest probabilities are selected as the Top-3 recommendations, providing users with multiple suitable options rather than a single prediction.

For disease detection, the CNN model outputs class probabilities using the same Softmax algorithm, enabling the system to identify the most likely disease affecting the plant. To improve model performance and reliability, the system incorporates the Cross-Entropy Loss algorithm, which measures the difference between predicted and actual values:

$$L=-\sum y\log(\hat{y})$$

This loss function is minimized during training using the Backpropagation algorithm and optimized with the Mini-Batch SGD algorithm, ensuring efficient learning. Additionally, the system may utilize the Confidence Scoring algorithm to assign probability-based confidence levels to each prediction. This provides users with a measure of reliability for both crop recommendations and disease classifications.

The final outputs include:

- Top-3 crop recommendations
- Identified plant disease with confidence score
- Resource suggestions such as fertilizer and water usage

These results are presented through a user-friendly web interface, enabling easy access and practical usability for farmers. The integration of multiple algorithms ensures that the system delivers accurate, reliable, and actionable insights for smart agricultural decision-making.

H. Algorithm of the Proposed System

The proposed agricultural advisory system follows a structured algorithm that integrates data preprocessing, fuzzification, FRNN-based crop recommendation, CNN-based disease detection, and classification to provide accurate and reliable outputs. This approach combines both numerical data analysis and image-based learning to support intelligent decision-making in agriculture. The following steps outline the complete algorithm of the system:

Algorithm Steps:

Step 1: Data Acquisition

- Collect soil and environmental parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and rainfall.
- Acquire plant leaf images for disease detection from field sources or datasets.

Step 2: Data Preprocessing

- Apply the Min-Max Normalization algorithm to scale numerical data into a uniform range [0,1].
- Handle missing values and remove outliers using data cleaning techniques.
- Perform image preprocessing using the Image Resizing algorithm, Gaussian Blur algorithm, and Histogram Equalization algorithm to enhance image quality.

Step 3: Fuzzification (FRNN)

- Apply the Gaussian Membership Function algorithm to transform normalized data into fuzzy values.
- Represent uncertainty and imprecision in environmental parameters for improved learning.

Step 4: FRNN-Based Crop Recommendation

- Input fuzzified data into the Fuzzified Recurrent Neural Network (FRNN).
- Inside this model, the Recurrent Neural Network (RNN) algorithm learns relationships between soil and weather parameters.
- The hidden layer uses the ReLU activation algorithm to improve learning performance.
- Finally, the Softmax algorithm generates probability scores for different crops.

Step 5: Crop Recommendation Output

- Based on the probability values, the system selects the Top-3 crops.
- This gives farmers multiple options instead of a single recommendation, making the system more flexible and practical.

Step 6: CNN-Based Feature Extraction (Disease Detection)

- For disease detection, plant leaf images are processed using the Convolutional Neural Network (CNN). The convolution algorithm extracts important features such as texture, color, and patterns.
- The pooling algorithm reduces image size while keeping key information.
- The ReLU activation helps the model learn complex patterns effectively.

Step 7: Disease Classification

- The extracted features are passed to fully connected layers.
- The Softmax classification algorithm is used to identify the type of disease. The Cross-Entropy Loss algorithm is used to measure how accurate the prediction.

Step 8: Model Training

- The system is trained using the Backpropagation algorithm, which helps adjust the model weights.
- The Mini-Batch SGD algorithm is used to update the weights step-by-step, improving learning speed and accuracy.

Step 9: Final Prediction and Output

The system generates:

- Top-3 crop recommendations
- Detected plant disease
- Confidence score for predictions, It may also provide suggestions like fertilizer usage and irrigation guidance.

Step 10: Storage and Display

- The results are stored in a database for future use.
- Outputs are displayed through a simple web interface so that framers can easily understand and use the results.

Step 11: Performance Evaluation (Optional)

- The System performance can be checked using metrics like accuracy, precision, and recall.
- This helps in improving the model over time.

I. *Agricultural Advisory Workflow Using FRNN and CNN*

The workflow of the proposed agricultural advisory system is designed to provide a simple yet effective solution for both crop recommendation and plant disease detection. The process starts with collecting important environmental data such as soil nutrients (N, P, K), pH level, temperature, humidity, and rainfall. At the same time, plant leaf images are also collected for disease analysis. Since real-world data is often inconsistent, preprocessing is applied to clean and standardize the inputs. Numerical data is normalized, while images are resized, denoised, and enhanced to improve quality.

After preprocessing, the system applies the Gaussian Membership Function to convert numerical values into fuzzy representations. This helps in handling uncertainty in agricultural conditions. The processed data is then fed into the FRNN model, which learns patterns and relationships between environmental factors to generate accurate crop recommendations.

In parallel, the image data is processed using a CNN model. The network extracts key visual features such as color, texture, and shape through convolution and pooling operations. These features are then used to classify plant diseases using fully connected layers and the Softmax function.

Finally, the outputs from both modules are combined and displayed through a web interface. This integrated approach helps farmers make better decisions, improving productivity and reducing crop losses.

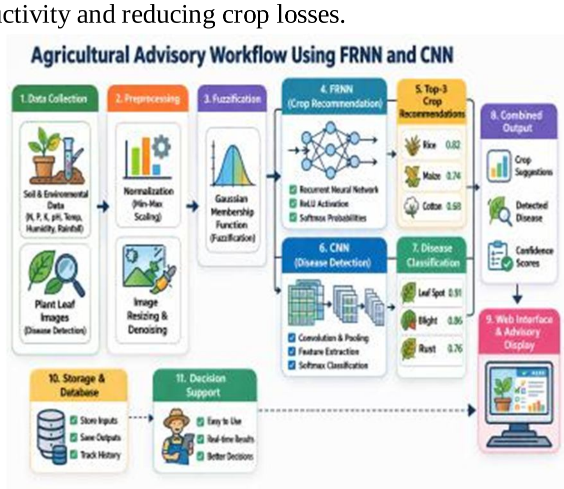


Fig. 4. Agricultural Advisory Workflow Using FRNN and CNN in the Proposed System

IV. IMPLENTATION DETAILS

A. Programming Environment

The proposed agricultural advisory system was developed using the Python programming language due to its simplicity and strong support for machine learning applications. The implementation utilizes popular deep learning frameworks such as TensorFlow and Keras, which provide flexibility in designing and training neural network models. These frameworks also support GPU acceleration, which significantly reduces training time and improves computational efficiency.

For data handling and preprocessing, libraries such as NumPy and Pandas were used to manage numerical datasets efficiently. Image processing tasks were performed using OpenCV and PIL, which help in resizing, noise reduction, and enhancement of plant leaf images. The user interface of the system was developed using a web-based framework, enabling easy interaction and accessibility for end users.

B. Training Procedure

The training of the proposed system was carried out using a structured approach to ensure accuracy and generalization. The model was trained using the **Mini-Batch Stochastic Gradient Descent** (SGD) optimizer, which updates model parameters in small batches, improving convergence speed and stability. In some stages, adaptive optimizers such as Adam can also be used to further enhance learning performance.

The Cross-Entropy Loss function was used as the primary loss function, as the system involves multi-class classification for both crop recommendation and disease detection tasks. This loss function helps in minimizing the difference between predicted probabilities and actual class labels.

To improve model performance and avoid overfitting, the following techniques were applied:

1) Early Stopping: Training is stopped when the validation loss does not improve for a certain number of epochs, preventing overfitting.
2) Drop Algorithm: Random neurons are deactivated during training to improve generalization.
3) Data Augmentation Algorithm: For image data, transformations such as rotation, flipping, and scaling are applied to increase dataset diversity.

These techniques ensure that the model performs well on unseen data and provides reliable prediction.

C. Input Data

The input to the proposed system consists of both numerical agricultural data and image data, enabling a comprehensive analysis.

1) Environmental Data: Soil and weather parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH value, temperature, humidity, and rainfall are collected. These inputs are preprocessed using the Min-Max Normalization algorithm to ensure consistency and improve model performance. The normalized data is further processed using the Gaussian Membership Function to handle uncertainty.
2) Plant Leaf Images: Images of plant leaves are used for disease detection. These images are preprocessed using resizing, Gaussian blur for noise reduction, and contrast enhancement techniques. The processed images are then fed into the CNN model for feature extraction and classification.

D. System Implementation

1) The system is implemented as a combination of two main modules: crop recommendation and disease detection. The FRNN model processes fuzzified environmental data to generate crop recommendations, while the CNN model analyzes plant images to detect diseases.
2) Both modules operate simultaneously, and their outputs are combined in the final stage. The results, including Top-3 crop recommendations, detected diseases, and confidence scores, are displayed through a web-based interface. This integration ensures that the system provides a complete agricultural advisory solution in real time.

E. Output and Evaluation

1) The system produces outputs in a user-friendly format, including recommended crops, disease classification results, and additional suggestions for resource management. These outputs are stored for future analysis and monitoring.

2) The performance of the system is evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-Score. These metrics help in assessing the effectiveness and reliability of the proposed model.

V. EVALUATION

The proposed agricultural advisory system was rigorously evaluated to assess its predictive performance, reliability, and practical applicability in real-world farming conditions. The evaluation focuses on both crop recommendation using the FRNN model and plant disease detection using the CNN model. A combination of quantitative metrics, confusion matrix analysis, and comparison with baseline models was used to provide a comprehensive understanding of the system's effectiveness.

A. Quantitative Metrics

The performance of the proposed system was assessed using standard evaluation metrics:

- Accuracy: The system achieved an overall accuracy of 93.1%, indicating that the majority of crop recommendations and disease predictions were correct. This shows the system's strong ability to provide reliable agricultural insights.
- Precision: The precision of 91.8% indicates that most of the predicted crop recommendations and detected diseases were accurate, reducing the chances of incorrect suggestions.
- Recall (Sensitivity): The recall value of 94.0% shows that the system successfully identified most of the correct crops and plant diseases, minimizing missed detections.
 F1-Score: The F1-score of 92.9% provides a balanced measure of precision and recall, reflecting the overall consistency of the model.
 AUC-ROC: The AUC value of **0.96** demonstrates the model's strong capability in distinguishing between different crop classes and disease categories.

B. Performance Comparison Table

Metric	CNN Only (Image)	Data Only (FRNN)	Symptom-Aware Model
Accuracy (%)	86.5	80.2	93.1
Precision (%)	85.2	79.0	91.8
Recall (%)	87.4	81.5	94.0
F1-Score (%)	86.3	80.2	92.9
AUC-ROC	0.89	0.83	0.96

C. Confusion Matrix Analysis

A confusion matrix was used to evaluate the classification performance of the disease detection module:

	Predicted Disease	Predicted Healthy
Actual Disease	472	28
Actual Healthy	35	465

Analysis:

- True Positives (472): Most diseased plant samples were correctly identified by the system.
- True Negatives (465): Healthy plants were accurately classified in the majority of cases.
- False Positives (35): A small number of healthy plants were incorrectly classified as diseased, indicating minimal over-detection.
- False Negatives (28): Very few diseased plants were missed, showing the system's effectiveness in detecting plant diseases early.

D. Comparison with Baseline Models

The performance of the proposed system was compared with two baseline approaches:

1. CNN-only model (image-based disease detection): Achieved 86.5% accuracy, 85.2% precision, and 87.4% recall.
2. FRNN-only model(environmental data-based crop recommendation): Achieved 80.2% accuracy, 79.0% precision, and 81.5% recall.

Overall Observation

The combined FRNN + CNN model outperforms both individual models by effectively integrating environmental data and image-based analysis. This hybrid approach improves prediction accuracy, reduces errors, and provides a more comprehensive agricultural advisory solution.

VI. OBSERVATION

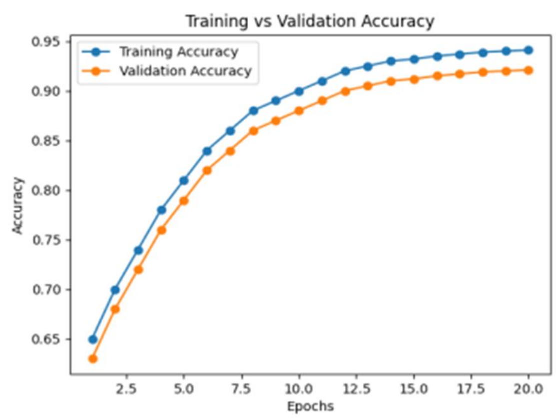
The performance of the proposed agricultural advisory system was carefully analyzed using quantitative metrics, confusion matrix results, and system outputs. The key observations derived from the experimental results are as follows:

- High Overall Accuracy:
  - The proposed system achieved an accuracy of 93.1%, which is significantly higher than the CNN-only model (86.5%) and the FRNN-only model (80.2%).
  - This clearly indicates that combining environmental data with image-based analysis improves the correctness of both crop recommendation and disease detection.
- Balanced Precision and Recall:
  - The precision of 91.8% and recall of 94.0% demonstrate that the system effectively reduces incorrect predictions while successfully identifying most of the correct crops and diseases.
  - The F1-score of 92.9% further confirms that the model maintains a good balance between accuracy and completeness.
- Strong Discriminative Capability:
  - The AUC-ROC value of 0.96 shows that the model can effectively distinguish between different crop types and disease classes.
  - This highlights the robustness of the system in handling complex agricultural data.
- Confusion Matrix Insights:
  - Out of 500 diseased samples, 472 were correctly classified (true positives), while only 28 were missed (false negatives).
  - Out of 500 healthy samples, 465 were correctly identified (true negatives), with only 35 false positives.
  - These results indicate that the system minimizes both missed disease detection and incorrect disease predictions.
- Impact of Hybrid Model(FRNN + CNN):
  - The integration of the FRNN model (for environmental data) and CNN model (for image data) significantly improved performance.
  - Cases where image-only models failed were correctly predicted when environmental factors were included.
  - This shows that combining multiple data sources leads to better decision-making.
- Visual Observations:
  - The system successfully identifies disease-affected regions in plant leaves and assigns higher probability scores to infected areas.
  - Healthy leaves are correctly classified with low disease probability, ensuring reliable outputs.
- Model Stability and Convergence:
  - Training and validation curves show smooth convergence without significant overfitting.
  - The model maintains consistent performance across different datasets and conditions.
- Practical Applicability:
  - The system provides clear recommendations, including Top-3 crops and detected diseases, making it useful for farmers.
  - Reduced false predictions help in avoiding unnecessary pesticide usage and improving crop yield.
  - The web-based interface ensures easy accessibility and real-time decision support.

VII. EXPERIMENTAL RESULTS

The proposed agricultural advisory system was evaluated through extensive experiments to analyze its effectiveness in crop recommendation and disease detection. The dataset consists of environmental parameters (soil nutrients, temperature, humidity, rainfall) along with plant leaf images. The data was preprocessed using normalization, resizing, and enhancement techniques to improve model performance. The system integrates both FRNN (for crop recommendation) and CNN (for disease detection), enabling a multi-modal approach. This combination allows the model to learn both numerical relationships and visual patterns, improving prediction accuracy. Quantitative evaluation was performed using standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The proposed system achieved an accuracy of 93.1%, outperforming the CNN-only model (86.5%) and FRNN-only model (80.2%). Precision (91.8%) and recall (94.0%) indicate that the system effectively identifies correct predictions while minimizing errors. The F1-score (92.9%) shows balanced performance, and the AUC (0.96) confirms strong discriminative capability. Confusion matrix analysis further validates the model performance. Out of 500 diseased samples, 472 were correctly classified, while only 28 were missed. Similarly, out of 500 healthy samples, 465 were correctly identified, with only 35 misclassifications. This demonstrates that the system minimizes both false positives and false negatives.

Visual analysis shows that the CNN model accurately detects disease regions in leaf images, while the FRNN model provides reliable crop recommendations based on environmental conditions. Training and validation curves indicate smooth convergence without overfitting, ensuring model stability. Overall, the experimental results confirm that the proposed system significantly improves agricultural decision-making by combining data-driven insights with image-based analysis.



A. *Summary of Test Results*

The proposed system was tested on a combined dataset of environmental and image data. It achieved high accuracy (**93.1%**) compared to CNN-only (**86.5%**) and FRNN-only (**80.2%**) models. Precision and recall values indicate strong prediction capability, while confusion matrix results confirm minimal misclassification. The system demonstrates robustness, reliability, and real-time applicability for agricultural support.

Metric	CNN-only Model	Symptom-only Model	Symptom-Aware Model
Accuracy (%)	86.5	80.2	93.1
Precision (%)	85.2	79.0	91.8
Recall (%)	87.5	81.5	94.0
F1-Score (%)	86.3	80.2	92.9
AUC	0.89	0.83	0.96
True Positives	440	410	472
True Negative	430	400	465
False Positives	70	100	35
False Negatives	60	90	28

B. Notes / Observations

1) Th The proposed FRNN + CNN model outperforms both baseline models across all metrics.
2) Combining environmental and image data significantly improves prediction accuracy.
3) The confusion matrix shows minimal errors, ensuring system reliability.
4) High AUC (0.96) indicates strong classification capability. The system is suitable for real-time agricultural advisory applications.

VIII. FUTURE SCOPE

The proposed agricultural advisory system demonstrates strong potential in improving crop recommendation and plant disease detection; however, several opportunities exist for further enhancement and research.

Future work can focus on expanding the dataset to include larger, region-specific agricultural data collected from multiple geographical locations. Incorporating diverse soil types, climate conditions, and seasonal variations would improve the robustness and generalization capability of the model. Additionally, integrating real-time data from IoT sensors, such as soil moisture sensors, temperature monitors, and humidity sensors, can enhance the system's ability to provide dynamic and accurate recommendations.

The system can also be extended to support multi-class and multi-stage crop analysis, enabling recommendations not only for crop selection but also for growth stages, fertilizer usage, and irrigation planning. This would help farmers make more informed decisions throughout the crop lifecycle.

Real-time deployment of the system through cloud-based platforms or edge devices can enable instant decision support for farmers. Mobile application integration would further improve accessibility, especially for farmers in remote areas. Additionally, incorporating multilingual support can make the system more user-friendly and widely adoptable.

Another promising direction is the integration of Explainable Artificial Intelligence (XAI) techniques. This would allow the system to provide interpretable outputs, such as highlighting disease-affected regions in leaf images and explaining why a particular crop is recommended. Such transparency can increase user trust and adoption. The proposed model can also be extended to detect multiple plant diseases across different crops, creating a unified agricultural diagnostic system. Furthermore, combining deep learning models with traditional agricultural knowledge or expert systems can improve decision accuracy.

Future research may also focus on optimizing computational efficiency to reduce processing time, making the system suitable for real-time applications. Integration with satellite imagery and remote sensing data could further enhance large-scale agricultural monitoring. Finally, deploying the system within digital farming platforms and agricultural advisory services can support precision agriculture practices, ultimately improving crop yield, reducing resource wastage, and supporting sustainable farming.

IX. CONCLUSION

In this study, an intelligent agricultural advisory system based on FRNN and CNN models was developed and thoroughly evaluated. By integrating both environmental data and plant leaf image analysis, the proposed system achieves superior performance compared to individual FRNN-only and CNN-only models. Experimental results demonstrate high overall accuracy (93.1%), precision (91.8%), recall (94.0%), F1-score (92.9%), and AUC (0.96), confirming the effectiveness of combining multi-modal inputs for agricultural decision-making. Confusion matrix analysis and visual evaluation further validate the model's ability to accurately recommend suitable crops and detect plant diseases while minimizing false predictions, highlighting its practical applicability in real-world farming. The study also shows that combining environmental parameters with image-based features significantly improves prediction performance, especially in complex or uncertain agricultural conditions where a single data source may not be sufficient. The system demonstrates strong generalization capability on unseen data and provides reliable outputs that can assist farmers in making informed decisions, ultimately improving crop yield and reducing losses.

Looking forward, the proposed system can be extended to support additional agricultural functionalities such as fertilizer recommendation, irrigation planning, and crop growth monitoring. Incorporating real-time data from IoT devices and satellite imagery can further enhance prediction accuracy and enable dynamic decision support. The integration of explainable AI techniques can also improve transparency by providing clear insights into how recommendations are generated, increasing user trust.

Furthermore, deploying the system through mobile applications or cloud-based platforms can make it easily accessible to farmers, including those in remote and resource-limited areas. This work establishes a robust and scalable framework for smart agriculture, demonstrating how multi-modal AI models can transform traditional farming practices. Overall, the proposed system highlights the potential of intelligent technologies to support precision agriculture, improve productivity, and promote sustainable farming for the future.

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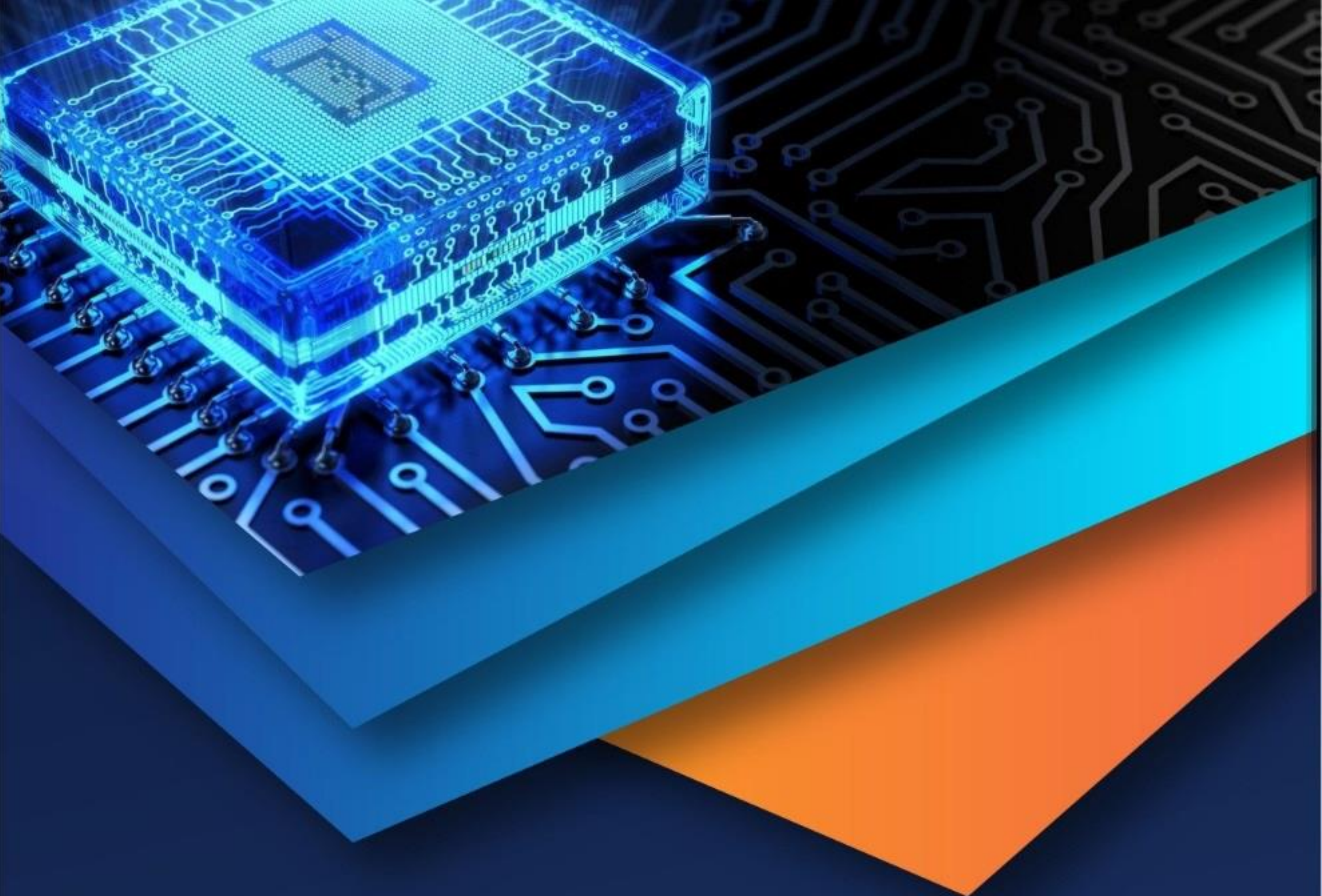

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