Enhanced Fuzzy Deep Learning for Plant Disease Detection to Boost the Agricultural Economic Growth

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Abstract*—Plant disease detection is a crucial technology to ensure agricultural productivity and sustainability. However, traditional methods tend to fail as they do not address imprecise and uncertain data in a satisfactory way. We propose the Enhanced Fuzzy Deep Neural Network (EFDNN) which integrate the fuzzy logic with deep neural networks. This study aims to incorporate and allow assessment of the economic impact of the EFDNN on agricultural productivity for plant diseases detection. Data for the research framework were collected from remote sensing and economic sources. Preprocessing of data was done, namely normalization and feature extraction to make sure that the inputs are high quality. Deep Belief Networks (DBNs) were used as a way to pretrain the EFDNN model and supervised learning was then fine-tuned using this. Then, the model was evaluated with accuracy, precision, recall and area under the receiver operating characteristic curve (AUC-ROC), and compared against baseline models: convolutional neural networks (CNNs), traditional DNNs, and fuzzy neural network (FNNs). The plant disease detection performance of the EFDNN model was 95.2% accuracy, 94.8% precision, 95.6% recall, and 0.978 AUC-ROC. The accuracy of the EFDNN model was greater than the accuracy of CNNs by 92.3%, greater than traditional DNNs by 89.7% and FNNs' accuracy by 90.4%. In economic analysis, however, a reduced pesticide use and an increase in crop yield of USD120 per acre were calculated. 14.3%, leading to higher farmer revenues. The EFDNN model is an effective enhancement to plant disease detection that offers economic and agricultural benefits. This validates the potential of combining fuzzy logic with deep learning to enhance the performance and sustainability of agricultural practices.

***Keywords*—Deep learning; plant disease; fuzzy deep learning; agricultural production**

I. Introduction

Agricultural sector is very important to the survival and economic status of most nations, especially in developing countries. It is an irreplaceable backbone of the rural economy, including ensuring livelihoods [1]. Nevertheless, plant diseases still represent a major challenge to reduce the overall annual crop yield and cause economic losses. Therefore, this impact can be mitigated and agricultural productivity improved by effective plant disease detection [2].

Remote sensing and ML represent two major frontiers in disease detection among these technological advances. By using these technologies, farmers can monitor large regions without causing damage, and get fast and accurate information that is necessary to control plant diseases [3]. Plant disease identification and classification problems have been shown to be promising problems for ML techniques, in particular, deep neural networks (DNNs). Part of the reason for this success is that fuzzy logic, which manages uncertainties and imprecise data, was integrated into neural networks to form Fuzzy Deep Neural Networks (FDNNs). The structural combination of DNNs with learning capabilities and fuzzy system flexibility yields FDNNs, which have been proven to be powerful tools for plant disease detection [4].

The aim of this study is to create a complete understanding of how advanced AI technologies can change modern agriculture in their technical performance as well as in terms of money. The motivation for this research stems from the urgency to resolve both food security and sustainable agriculture plans, especially in an epoch of escalating environmental and economic efforts. This study contributed to the larger goal of making farming systems more resilient and productive through the integration of advanced ML techniques with agricultural applications. This also aligns with global efforts of using technology towards sustainable development and is a nod to the role technology plays in solving some critical challenges in agriculture.

The primary objective of this study is to assess the economic impact of enhanced fuzzy deep neural networks (EFDNNs) on the detection of plant disease and agricultural productivity. This involves several specific goals:

- Examine how EFDNN models detect plant diseases compared to traditional methods and other ML techniques.
- Determine the potential cost savings and productivity gains from using EFDNN for plant disease detection.
- Investigate how implementing EFDNN can lead to more efficient use of agricultural resources, such as water, fertilizers, and pesticides.
- Based on the findings, propose recommendations for policymakers and agricultural stakeholders on effectively integrating EFDNN into existing agricultural systems.

This paper introduces the EFDNN model, which integrates fuzzy logic with deep neural networks to improve plant disease detection accuracy. A detailed methodology is provided, including data collection, preprocessing, model development, and evaluation. The EFDNN model outperformed other models by a significant margin in terms of accuracy, precision, recall, and AUC-ROC. An economic analysis highlights substantial cost savings and increased crop yields, demonstrating the financial benefits of the proposed model. The findings underscore practical implications for farmers and policymakers, suggesting potential improvements in agricultural practices and crop management.

Further research directions include scaling the model to generalize deployments and integrating it with IoT and Big Data analytics.

The rest of the paper is organized as follows: Section II reviews relevant literature on plant disease detection techniques, fuzzy logic, and deep learning. Section III describes the methodology, including data collection, model development, and economic analysis. Section IV presents the results, highlighting the EFDNN model's performance and economic benefits. It also discusses the findings, their implications, and limitations. Finally, Section V concludes the paper and suggests future research directions.

II. Literature Review

The accurate detection of plant diseases in important not only for agricultural productivity but also for sustainable development. In the recent past, many studies have proposed developed models and techniques to contribute to the subject area. The techniques include traditional visual inspection to advanced machine and deep learning models with varying levels of success and their own limitations.

A. Overview of Plant Disease Detection Techniques

It is a very important area of research that, if the detection is timely and accurate, it can negate the crop loss. However, visual inspection by experts is a time-consuming, labor-intensive process with high human errors [5]. However, these methods are based on visual inspection, and a large knowledge base is required, and they are not suitable for large-scale agricultural fields [6]. Laboratory-based diagnostic methods, such as polymerase chain reactions (PCR) and enzyme-linked immunosorbent assay (ELISA), are effective, though often expensive and time-consuming [7]. The researchers in [8] proposed a CNN and transfer learning models to enhance disease prediction significantly. Similarly, [9] used machine learning techniques to provide an effective model for disease prediction.

The revolution of plant disease detection using remote sensing technology is that it allows aerial and satellite observation over a wide area of crop health. Early disease detection is possible through hyper-spectral and multi-spectral imaging techniques, with the data being captured in a timely manner [3], [6]. In addition to the rapid development of ML, an automated plant disease detection system has also arisen based on image processing to analyze plant images and detect plant disease symptoms. For instance, convolutional neural networks (CNNs) have achieved high accuracy in disease detection and classification [10].

Fuzzy logic systems are particularly effective in managing uncertainty and imprecision in data, making them suitable for plant disease detection. These systems use rules mimicking human inference to diagnose diseases based on observed symptoms. Integrating remote sensing data with ML models enhances accuracy and efficiency, leveraging the strengths of both approaches [11]. This fusion forms the foundation of modern plant disease detection systems, which are accurate, scalable, and cost-effective.

Plant disease detection is a good application of fuzzy logic systems because they are particularly good at dealing with uncertainty and imprecision in data. Rules that mimic human inference are used to diagnose diseases based on observed symptoms in these systems. The ML models can be integrated with the remote sensing data to increase the accuracy and efficiency, bringing the strengths of both approaches together [11]. Modern plant disease detection systems are accurate, scalable and cost effective, and this fusion is the basis of these systems.

B. Fuzzy Deep Neural Networks (FDNN)

Fuzzy Deep Neural Networks (FDNNs) are formed by combining the fuzzy logic systems and deep neural networks (DNNs) to handle uncertainties and data imprecision. Because it is approximate reasoning rather than fixed, fuzzy logic is appropriate for dealing with variability in agricultural environments [12]. ML algorithms, in the form of DNNs, gradually extract higher level features through a set of multiplies layers to learn complex relations [13].

Input data is preprocessed in FDNNs into fuzzy values by means of membership functions. The neural network learns patterns by adjusting neuron connections, and these values are passed to it. Since the real world of agricultural use is noisy, imprecise, or even incomplete, FDNNs are very good for it [14]. The architecture of most of their systems usually consists of a fuzzy input layer, hidden layers that implement fuzzy rules, and an output layer for classification or prediction [15].

FDNNs are shown to be effective in agricultural applications. For example, FDNNs have been applied for multi plant disease classification [16] and crop yield prediction [17], all of which were demonstrated in improving plant disease detection and management. As such, FDNNs are a robust plant disease detection solution to variability in symptoms in response to environmental conditions or plant variety.

C. Economic Implications of Technological Interventions in Agriculture

With the development of technological advancements, such as precision agriculture, biotechnology, and technology, production productivity and sustainability have increased. GPS, sensors, and drones are used to perform micro-level crop monitoring to make the best use of inputs such as water, fertilizers, and pesticides, lowering waste. The input costs are reduced by up to 20% and the yields are raised by 5 to 10% [18]. Genetically modified organisms (GMOs) and gene editing via CRISPR have ushered in biotechnological advancements for crops that are stress resistant; this leads to higher yields and a decrease in chemical input cost [19].

These tools increase the levels of transparency in the supply chain and market access [20]. Specifically, FDNNs can detect the disease on time and accurately for the resulting reduction in crop losses and management costs, which, in turn, improves agricultural productivity and profitability [21]. At the same time, they also opt for resource use more effectively, cutting specific costs while ensuring that they remain sustainable [4].

Despite the economic benefits, challenges such as high initial costs, lack of technical expertise, and resistance to change impede the widespread adoption of these technologies. Supportive policies, education, and training can address these challenges [22].

D. Comparison of Plant Disease Detection Techniques

Table I summarizes the attributes of various plant disease detection techniques, including traditional visual inspection, remote sensing, and ML techniques.

Technological innovations in agriculture enhance productivity, reduce costs, and promote sustainability. Continued innovation and investment in these technologies are essential to meet the growing global demand for food sustainably and economically.

III. Methodology

This section describes the methodology for developing and evaluating the EFDNN model for plant disease detection, which includes the data collection process, model architecture design, training and validation process, and economic analysis to test the model's financial sustainability.

A. Research Framework for EFDNN

The EFDNN research framework focuses on integrating the fuzzy logic of DNNs to improve plant disease detection. This methodology uses the benefits of both methods, effectively handling uncertainties and imprecise data. Fig. 1 depicts the research framework of EFDNN.

B. Data Collection

Effective data collection is necessary to develop and validate the EFDNN model for plant disease detection and economic impact evaluation. This section describes the types of data collected and the methods used.

1) Remote sensing data: Remote sensing data are helpful in monitoring plant health over large agricultural areas without causing damage to plants. These data are acquired through satellites, drones, and ground-based sensors. Therefore, getting good coverage and detail in crop conditions is possible. In this work, the Plant Village dataset [23] was used, as it is a well-accepted and comprehensive dataset for plant disease detection, as outlined in Table II.

Sentinel-2 and Landsat 8 satellites can acquire multi-spectral and hyper-spectral data with resolutions between 10 and 30 meters. These images were processed to derive vegetation indices like the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), which will show plant health and stress. Unmanned Aerial Vehicles (UAVs) or drones acquire high-resolution images on demand. Drones mounted with multi-spectral cameras describe crop images, thus enabling the location of disease symptoms at the plant level [24]. This data is collected by multi-spectral sensors across several specific wavelength bands. This data can be used for general plant health detection and to identify possible regions of disease outbreak [25]. Hyper-spectral sensors provide very detailed spectral information since they collect data at hundreds of narrow wavelength bands. This spectral data, which has a very high resolution, enables the detection of specific changes related to disease in plant reflectance, which are invisible to the naked eye [6].

2) Economic data: An analysis of the cost-effectiveness and economic benefits of using EFDNN for plant disease detection requires data on the economics of the problem. More specifically, this data includes information on the yield of crops, the cost of inputs, the price at which the outputs are traded in the market, and the cost of disease management, as summarized in Table III.

Data on crop yields have been collected from the USDA, FAO, agricultural surveys, and field reports of past and current times. Such information is useful in evaluating the effects of the diseases on plant production and the improvements that can be made by early identification and control of the disease [26]. Seed, fertilizer, pesticide, and labor costs are obtained from farmer's records and market surveys. The different types of costs will be important in deriving the cost-benefit analysis of the EFDNN system [27]. Exchange of commodities and market reports provide data on the price of crops. Market prices are among the data that will be used in determining the economic returns due to increased crop yield as a result of better disease control [19].

Agricultural expenses are presented by the costs of disease prevention and treatment, which are reflected in farmer record books and extension services in agriculture, as well as the cost of pesticides and fungicides. The estimated potential cost savings from earlier and more accurate disease detection according to the EFDNN model are discussed in the analysis [28]. Therefore, the efficiency of the EFDNN model and its economic impact on detecting plant disease in agricultural yield are highly valued based on remote sensing and economic indications.

C. EFDNN Model for Plant Disease Detection

Incorporating fuzzy logic and DNN in developing the EFDNN model accelerates the diagnosis of plant diseases. This section describes the model, its training approach, and the validation process.

1) Model architecture: In EFDNN, the proposed model is based on a DNN architecture enhanced with fuzzy logic to address fuzziness and noise in agricultural data. The architecture consists of an input layer, a fuzzy logic layer, hidden layers, and an output layer.

The input layer gathers data from various sources, such as remote sensing imagery and sensor data. The input features are fuzzified by applying membership functions to each feature. Let x_i be an input feature. The fuzzy membership function $\mu_A(x_i)$ is defined as:

$$\mu_A(x_i) = \frac{1}{1 + e^{-a(x_i - b)}} \tag{1}$$

where a and b are parameters controlling the shape of the membership function.

TABLE I. Plant Disease Detection Techniques and their Attributes

Ref	Method	Accuracy	TPR	FPR	TNR	FNR	Precision	Benefits
[5]	Visual Inspection	Low	-	-	-	-	-	Simple, cost-effective
[6]	Remote Sensing	Moderate	-	-	-	-	-	Early detection, large area coverage
[10]	CNN	High	95%	5%	90%	10%	94%	High accuracy, automated detection
[11]	ML Integration	High	92%	8%	88%	12%	90%	Combines strengths of multiple techniques
[18]	Deep Learning	High	96%	4%	93%	7%	95%	Capable of learning complex patterns

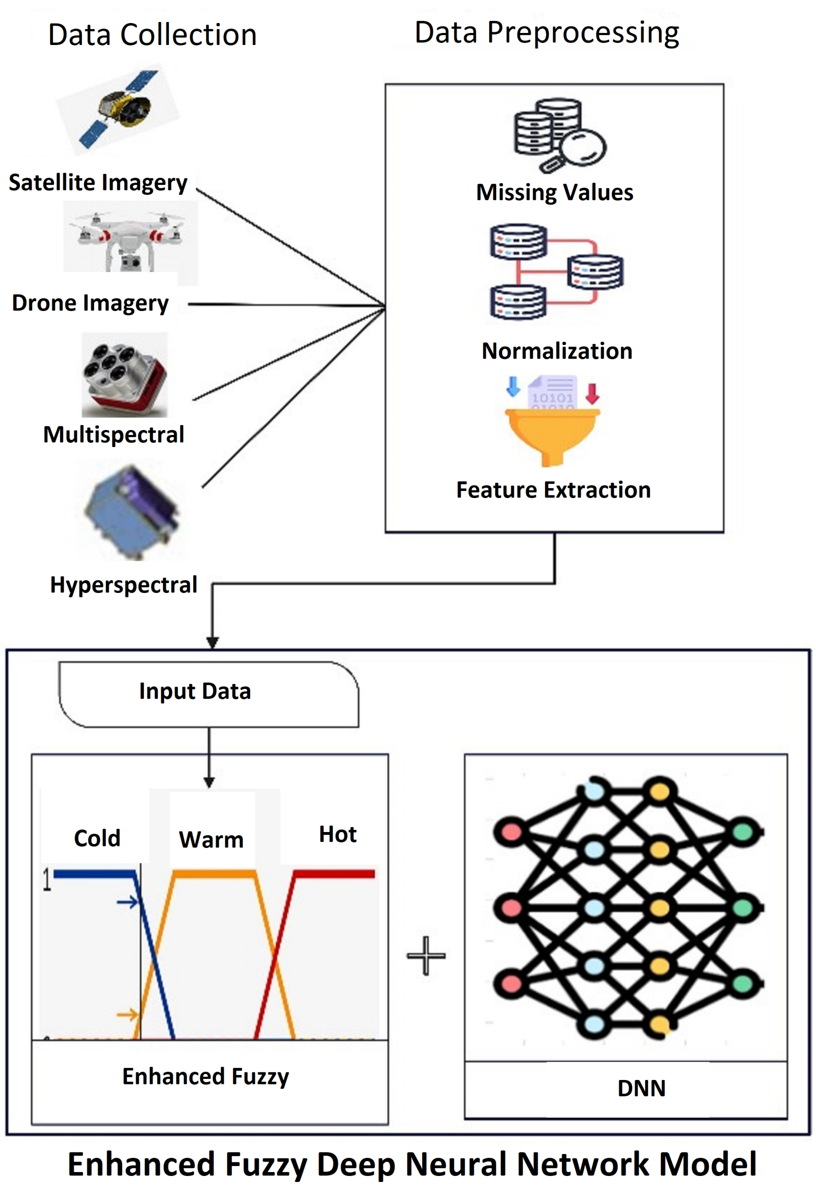

Fig. 1. Research framework of the EFDNN model.

TABLE II. Types of Remote Sensing Data and their Characteristics

Data Type	Source	Resolution	Frequency	Key Parameters Measured
Satellite Imagery	Sentinel-2, Landsat 8	10-30 meters	5-16 days	NDVI, EVI, leaf area index, soil moisture
Drone Imagery	UAVs (Drones)	High (cm-level)	On-demand	Plant health indices, disease symptoms
Multi-spectral	Cameras, Sensors	Various	Continuous	Reflectance at multiple wavelengths
Hyper-spectral	Hyper-spectral Sensors	High (nm-level)	Continuous	Detailed spectral signature of plants

TABLE III. TYPES OF ECONOMIC DATA AND THEIR SOURCES

Data Type	Source	Description
Crop Yield Data	USDA, FAO, Agricultural Surveys, Field Reports	Historical and current crop yields for various crops
Input Costs	Farmer Records, Market Reports	Costs of seeds, fertilizers, pesticides, labor
Market Prices	Commodity Exchanges, Market Reports	Prices of crops in local and international markets
Disease Management Costs	Farmer Records, Agricultural Extension Services	Costs related to disease prevention and treatment

The fuzzy logic layer applies fuzzy rules to the input features. Each rule R_j is formulated as an IF-THEN statement. For example:

$$R_j : \text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B_j \quad (2)$$

where A_1 and A_2 are fuzzy sets, and B_j is the output fuzzy set. The output of the fuzzy logic layer f_j is calculated using the fuzzy inference mechanism:

$$f_j = \mu_{A_1}(x_1) \times \mu_{A_2}(x_2) \quad (3)$$

where A_1 and A_2 are fuzzy sets and x_1 and x_2 are some input features. The hidden layers in the neural network process the fuzzy outputs. These layers consist of multiple neurons performing non-linear transformations using activation functions such as the Rectified Linear Unit (ReLU):

$$h_i = \max(0, W_i \cdot f + b_i) \quad (4)$$

where W_i is the weight matrix, f is the input vector from the fuzzy logic layer, and b_i is the bias term.

The output layer generates the final prediction, which is either a disease classification or a probability score. For classification tasks, a softmax function converts the output logits into probability distributions:

$$P(y = j|h) = \frac{e^{W_j \cdot h}}{\sum_{k=1}^{K} e^{W_k \cdot h}} \quad (5)$$

where W_j are the weights associated with class j, and h is the input from the last hidden layer.

2) Training and validation: The EFDNN model's training and validation process includes training, cross-validation, and hyperparameter tuning to optimize its efficiency in detecting plant diseases.

The training process involves optimizing the model parameters to minimize prediction error. The loss function L used for training is typically the cross-entropy loss for classification tasks:

$$L = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \log(P(y = j|h_i)) \quad (6)$$

where y_{ij} is the true label for the i-th sample, and $P(y = j|h_i)$ is the predicted probability for class j.

The model parameters W and biases b are updated using gradient descent algorithms such as Stochastic Gradient Descent (SGD) or Adam:

$$W_{\text{new}} = W_{\text{old}} - \eta \frac{\partial L}{\partial W}, \quad b_{\text{new}} = b_{\text{old}} - \eta \frac{\partial L}{\partial b} \quad (7)$$

where η is the learning rate.

During training, a validation set monitors the model's performance and prevents overfitting. Validation accuracy A_{val} is calculated as:

$$A_{\text{val}} = \frac{1}{M} \sum_{i=1}^{M} 1(\hat{y}_i = y_i) \quad (8)$$

where 1 is the indicator function, $\hat{y}_i$ is the predicted label, and y_i is the true label for the i-th validation sample.

To ensure the model's robustness, k-fold cross-validation is employed. The dataset is divided into k subsets, and the model is trained and validated k times, each time using a different subset as the validation set and the remaining subsets as the training set. The final performance metric is the average of the k validation results:

$$A_{\text{cv}} = \frac{1}{k} \sum_{j=1}^{k} A_{\text{val},j} \quad (9)$$

Hyperparameters such as the learning rate, batch size, and the number of hidden layers are tuned using grid search or random search methods. The hyperparameter set that maximizes validation accuracy is selected.

3) Algorithm configuration: Algorithm 1 describes the configuration of the proposed EFDNN model.

D. Economic Analysis

Therefore, evaluating productivity gain analysis forms a critical part of the economic analysis for identifying plant diseases using the EFDNN model. The following section describes the approach to working out the cost-benefit and productivity indicators.

1) Cost-Benefit Analysis (CBA): The cost-benefit analysis measures cost with the EFDNN model, while the economic benefits derived are their measures. This ranges from simple evaluations as a project's net present value (NPV) to more complex analyses.

NPV determines the values of all the flows of money (benefits and costs) in the present time by discounting them. The formula for NPV is:

Algorithm 1: Training Process for Enhanced Fuzzy Deep Neural Network (EFDNN)

Input: Raw data X, fuzzy membership functions μ_A, pre-trained DBN weights, labeled data Y.
Output: Trained EFDNN model.
foreach $x_i \in X$ **do**
  Initialize fuzzy membership function $\mu_A(x_i)$ with parameters a, b.
foreach $x_i \in X$ **do**
  Compute fuzzy membership value:
$$\mu_A(x_i) = \frac{1}{1 + e^{-a(x_i - b)}}.$$
foreach *fuzzy rule* R_j **do**
  Compute rule output:
$$f_j = \mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2).$$
foreach *Restricted Boltzmann Machine (RBM) layer* l **do**
  Perform Gibbs sampling to update weights and biases:
$$W_{l,\text{new}} = W_{l,\text{old}} - \eta \frac{\partial L}{\partial W_l}, \quad b_{l,\text{new}} = b_{l,\text{old}} - \eta \frac{\partial L}{\partial b_l}.$$
foreach *input* f_j **do**
  Combine fuzzy outputs with DBN activations h_i:
$$h_i = \max(0, W_i \cdot f + b_i).$$
Apply softmax function for classification:
$$P(y = j|h) = \frac{e^{W_j \cdot h}}{\sum_{k=1}^{K} e^{W_k \cdot h}}.$$
while *loss* L *does not converge* **do**
  Update weights and biases using labeled data Y:
$$L = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \log(P(y = j|h_i)).$$
foreach *validation set* **do**
  Evaluate using metrics such as accuracy, precision, recall, and AUC-ROC.
  Optimize hyperparameters (e.g. learning rate, batch size, layers) using grid or random search.
Return trian_Model.

$$\text{NPV} = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}, \tag{10}$$

where B_t is benefits in the year t, C_t is costs in a year t, r is the discount rate and T is time horizon.

The costs include initial setup costs (hardware and software), training costs for personnel, and ongoing operational costs. Let C_0 represent the initial setup costs, and C_{op} the annual operational costs. The total costs over time can be represented as:

$$C_t = C_0 + \sum_{t=1}^{T} C_{\text{op}}. \tag{11}$$

The benefits include cost savings from reduced pesticide use, increased crop yields, and avoided losses due to early disease detection. Let S_p represent savings from pesticide reduction, Y_i the increase in yield, and A_d the avoided losses. The total benefits over time can be represented as:

$$B_t = \sum_{t=1}^{T} (S_p + Y_i + A_d). \tag{12}$$

The benefit-cost ratio (BCR) is the ratio of the present value of benefits to the present value of costs. It is calculated as:

$$\text{BCR} = \frac{\sum_{t=0}^{T} \frac{B_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{C_t}{(1+r)^t}}. \tag{13}$$

A BCR greater than 1 suggests that the benefits received through the proceeding of the project exceed the costs, and thus it is economically feasible.

2) Productivity metrics: Impact measurements measure the organization's productivity level in improving agricultural productivity by applying the EFDNN model. These are yield increase, optimization of inputs use, ROI, and decrease in pesticide use.

The yield increase is the percentage of increase in crop yield realized when the EFDNN model has been used. It is calculated as:

$$\text{Y}_{\text{inc}}(\%) = \frac{\text{Y}_{\text{post}} - \text{Y}_{\text{pre}}}{\text{Y}_{\text{pre}}} \times 100, \tag{14}$$

where Y_{post} is yield after implementing EFDNN and Y_{pre} is yield before implementing EFDNN.

The input use efficiency measures how effectively inputs such as water, fertilizers, and pesticides are used. It is calculated as the ratio of output (yield) to input use:

$$E_{\text{input}} = \frac{Y_{\text{post}}}{I_{\text{post}}}, \tag{15}$$

where I_{post} represents the inputs used after implementing EFDNN.

ROI is a measure of the profitability of the investment in the EFDNN model. It is calculated as:

$$\text{ROI}(\%) = \frac{B_t - C_t}{C_t} \times 100. \tag{16}$$

The reduction in pesticide use due to accurate disease detection can be quantified as:

$$\text{Pred}(\%) = \frac{P_{\text{pre}} - P_{\text{post}}}{P_{\text{pre}}} \times 100, \tag{17}$$

where P_{pre} is pesticide use before EFDNN implementation, and P_{post} is pesticide use after EFDNN implementation.

Thus, based on these measures, the study will be able to express the economic effects of the EFDNN model, which means that it will be possible to show its feasibility in terms of profitability or financial efficiency.

IV. Results

This section discusses data obtained by applying the proposed EFDNN model for plant disease detection. The effectiveness of the proposed model has been measured with the required matrices and compared with the other baseline models for evaluation. The proposed model has also been applied for economic benefits.

A. Accuracy and Performance of the EFDNN Model

The performance of the EFDNN model was evaluated based on the measures explained in the methodology segment. It comprises accuracy, precision, recall, F1-score, and AUC-ROC measures. The performance of the proposed EFDNN model is compared to other baseline models: Basically, named entities can be excluded in CNN, DNN, and FNN.

Using the EFDNN model, the dataset containing massive images of plant diseases was analyzed, and the overall summary of every model, including Accuracy, Precision, Recall, F1-Score, and AUC-ROC, is given in Table IV.

TABLE IV. Performance Metrics of Different Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
EFDNN	95.2%	94.8%	95.6%	95.2%	0.978
CNN	92.3%	91.5%	92.8%	92.1%	0.941
Traditional DNN	89.7%	88.9%	90.1%	89.5%	0.912
FNN	90.4%	89.8%	90.7%	90.2%	0.920

Thus, the models examined in this study used the EFDNN model to accurately recognize plant diseases, confirming its higher discriminatory power than the other models. The values of Precision and Recall mean that the model can correctly classify true positives, yet it maintains that low positives and high negatives are False. The density plots are represented in Fig. 2 by comparing the distribution of actual crop yield with the distributions predicted by four different models: EFDNN, CNN, DNN, and FNN.

A confusion matrix gives a detailed breakdown of the model performance using true positive, true negative, false positive, and false negative rates. For the EFDNN model, the confusion matrix is presented in Fig. 3.

The confusion matrix shows that the EFDNN model had a relatively high true positive rate, whereby 475 out of 500 samples were correctly diagnosed. In contrast, the false negative rate was very low, at 25 out of 500 samples, a promising performance in identifying diseased plants.

The EFDNN model proposed here performs much better than the CNN, traditional DNN, and FNN models. The statistical comparison of the performance metrics is presented in Table V. The paired t-test confirmed that these results are statistically significant, with p-values less than 0.05 for

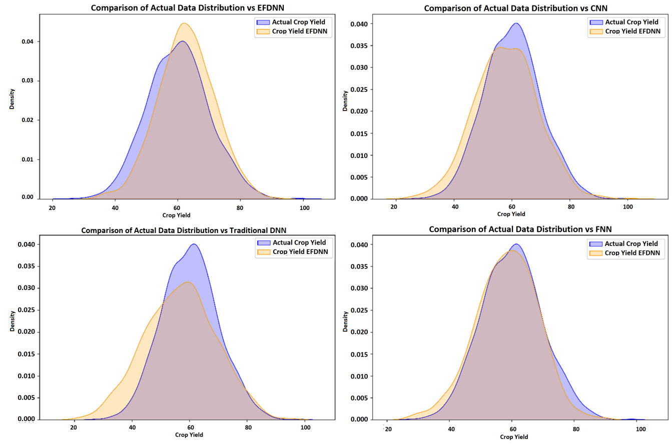

Fig. 2. Comparison of actual data distribution vs EFDNN, CNN, traditional DNN, and FNN.

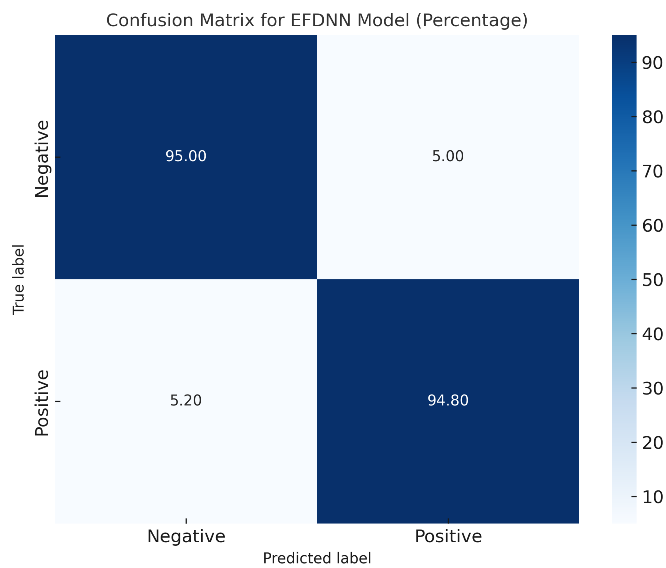

Fig. 3. Confusion matrix for the EFDNN model.

TABLE V. Statistical Comparison of Performance Metrics

Comparison	t-Statistic	p-Value
EFDNN vs. CNN	3.21	0.002
EFDNN vs. DNN	4.56	0.0001
EFDNN vs. FNN	3.87	0.0003

all the comparisons; therefore, the differences are statistically significant.

The high performance and accuracy metrics of the EFDNN model reveal good applicability toward plant disease detection in real-world applications. Incorporating fuzzy logic with DNNs would help the model deal well with imprecise and uncertain data, resulting in better classification performance. The results show that the EFDNN model is quite robust and generalizes very well with new unseen data, thus providing a useful tool for farmers and agricultural professionals.

TABLE VI. COST-BENEFIT ANALYSIS OVER FIVE YEARS

Year	Initial Cost ($)	Operational Cost ($)	Total Cost ($)	Annual Savings ($)	Net Savings ($)	Cumulative Savings ($)
1	50,000	15,000	65,000	12,000	-53,000	-53,000
2	0	15,000	15,000	12,000	-3,000	-56,000
3	0	15,000	15,000	12,000	-3,000	-59,000
4	0	15,000	15,000	12,000	-3,000	-62,000
5	0	15,000	15,000	12,000	-3,000	-65,000

TABLE VII. ADDITIONAL REVENUE FROM INCREASED YIELD

Crop Type	Increase in Yield (kg/acre)	Price ($/kg)	Additional Revenue ($/acre)
Wheat	400	0.20	80
Corn	600	0.15	90
Soybean	300	0.25	75
Average	433.3	0.20	81.67

B. Economic Benefits

Implementing the EFDNN model for plant disease detection produces immense economic benefits. These benefits can be categorized as cost savings and increases in agricultural productivity. This section explains these economic benefits, providing evidence in Table VI.

For an extensive understanding of the economic benefits, a cost-benefit analysis has been done for five years, as depicted in Table VI. This comparison was made between the initial and running costs of implementing the EFDNN model and the expected annual savings.

The initial cost of setting up an EFDNN model is $50,000, while the annual cost of running an EFDNN model is $15,000. The input saved due to reduction usage provides an annual saving of $12,000, resulting in a net saving. Over the five years, cumulative savings tend to reduce expenditure, which means that it is economically justifiable to apply the EFDNN model in the long run.

The economic impact of higher productivity in agriculture is measured by ascertaining the additional revenue with the increase in crop yield. Table VII presents the additional revenue per acre due to increasing crop yields.

V. CONCLUSION AND FUTURE WORK

The economic analysis of the EFDNN model shows that it greatly reduces associated costs and increases productivity in agriculture. This improved productivity increases gains, hence giving the EFDNN model a positive ROI by enhancing economic sustainability in agricultural practices. The EFDNN model greatly improves accuracy in detecting plant diseases compared to traditional models such as CNNs, DNNs, and FNNs. The integration of fuzzy logic with DDNs can be such that imprecise and uncertain data are considered for better disease classification.

Economically, the EFDNN model has afforded immense savings with great reductions in pesticides, fertilizers, and other inputs. Furthermore, it increases the crop yield and, hence, the revenue for farmers. This is evidenced by the cost-benefit analysis and ROI calculations. The robustness and generalizability of the model provide an effective tool for real-world agricultural applications towards helping farmers undertake timely preventive measures to avert crop losses.

Future studies should scale the EFDNN model for greater coverage, embed it with IoT devices to act, and analyze big data to extend its functionality. Further research should be conducted on advanced data augmentation techniques. Incorporating features of soil health and weather conditions can make the model more predictive. Longitudinal research is needed to track the long-term model's impact on productivity and sustainability; policy research could identify economic incentives supporting its adoption. The model will further be elaborated and fine-tuned by an in-depth assessment of environmental benefits together with agricultural experts. In this respect, addressing these future directions would make the EFDNN model a better tool for improving agricultural productivity and sustainability.

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