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Digital Platform for Crop Health and Agricultural Services

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ABSTRACT- Modern precision agriculture requires the incorporation of high-accuracy diagnostic instruments to guarantee food security for inexperienced practitioners. This paper introduces an AI-driven agricultural web architecture that connects deep learning-based diagnostics with real-world farm management. The main contribution is a Convolutional Neural Network (CNN) framework that can automatically find diseases in five common crops: Capsicum annuum, Vitis vinifera, Zea mays, Solanum tuberosum, and Solanum lycopersicum. The proposed model reached a final training accuracy of 98.30% and a validation accuracy of 90.12% over 10 epochs by using a sequential architecture with optimized convolutional layers and data augmentation. The platform has a localized marketplace, a government scheme eligibility engine, and a Crop Journal for long-term record-keeping to make it useful in the real world.
Results demonstrate that this unified ecosystem provides a transparent and accessible framework for data-informed agricultural management, effectively lowering the technical barrier for new farmers.

KEYWORDS- Deep Learning; Plant Disease Detection; Convolutional Neural Networks; Plantvillage Dataset; Image Classification; Precision Agriculture.

I. INTRODUCTION

Agriculture is an essential part of developing economies, especially in countries like India where many people rely on farming for their livelihoods. However, this sector is facing several challenges, such as serious crop diseases, unpredictable weather, and limited market access [1], [2], [17]. The quick growth of mobile technology in rural areas has opened up new opportunities, but the agricultural tools available are still scattered and not very effective. Farmers often have to use various apps for disease diagnosis, weather updates, and market transactions, which adds to their workload and makes it hard for small-scale and new farmers to manage [4], [5].

Food security is heavily affected by plant diseases, which can significantly lower crop yields depending on the location [1], [3]. Traditional diagnostic methods depend on manual checks by trained experts. This process can be slow, expensive, and often out of reach for those in remote areas [10], [12]. Moreover, agricultural supply chains involve several middlemen, which prevents direct contact between producers and consumers and creates inefficiencies, as seen in recent global supply chain issues [17].

There is a clear need for a connected and smart digital platform that pairs expert-level artificial intelligence with vital agricultural services. This paper presents the Digital Platform for Crop Health and Agricultural Services. This platform combines various functions into one system, offering a centralized solution for managing agriculture. It features a Convolutional Neural Network (CNN) model that can detect multiple plant diseases in real time using images [3], [10], [12], [16], [19], [20].

Additionally, the system includes a conversational AI agent that acts as a virtual farm advisor and is available 24/7. The platform allows direct transactions between farmers and consumers through a dedicated marketplace. It also supports organized farm record management and provides real-time access to weather information and agricultural insights through external APIs. The system uses a scalable NoSQL Firebase architecture for efficient data management and user profile handling.

The main goal of this research is to create an inclusive and scalable framework that helps reduce the digital divide, allowing farmers with limited access to technology to make informed decisions.

In below Figure 1 illustrates the architectural workflow and functional modules of the proposed integrated agricultural platform. The remainder of this paper is structured as follows: Section II reviews related work in agricultural artificial intelligence, Section III explains the proposed methodology with a focus on CNN design and data preparation, and Section IV presents the experimental results and performance evaluation.

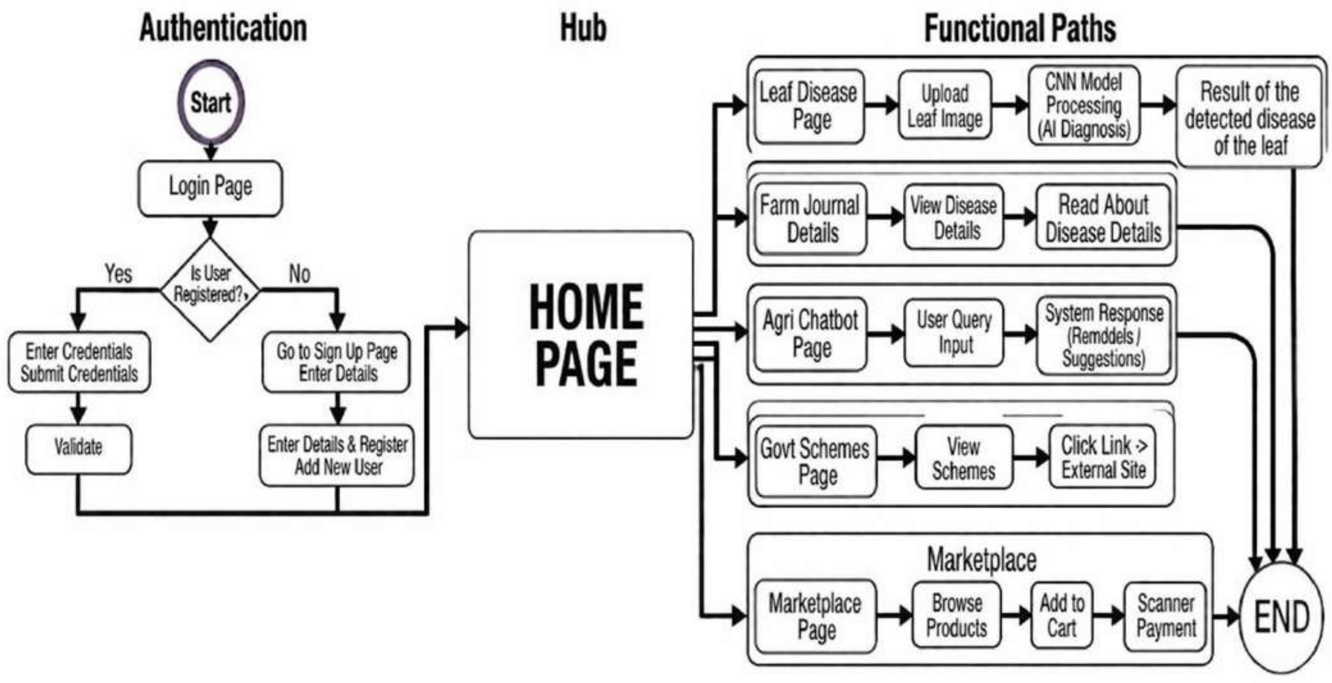

Figure 1: Architectural Workflow and Functional Modules of the Integrated Agricultural Platform.

II. RELATED WORK

The evolution of digital agriculture has progressed from simple rule-based systems to advanced data-driven deep learning architectures. This section presents a comprehensive analysis of the current research landscape, focusing on automated diagnostics, architectural optimization, and integrated agricultural service platforms.

A. Comparative Analysis of Deep Learning Architectures

Automated disease identification has become a critical area in reducing global crop yield losses. Benchmark datasets such as PlantVillage, which consists of over 50,000 labeled images across multiple classes, are widely used for evaluating model performance. Studies comparing Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) models indicate that CNNs generally outperform LSTMs in spatial feature extraction tasks [4], [7], [9],[19].

Several works have reported high validation accuracies exceeding 99% under controlled conditions [1], [3], [10]. However, a major limitation identified in existing models is their "black-box" nature, where predictions lack interpretability. For instance, while a CNN may accurately detect a necrotic lesion on plant leaves, it cannot effectively explain the reasoning behind its classification to end users. Addressing this limitation, the proposed work focuses on improving feature transparency and computational efficiency through optimized convolutional architectures.

B. Transfer Learning and Real-World Constraints

Transfer learning techniques using pre-trained models such as ResNet, VGG, and Inception-based architectures have been widely adopted to address the limitations of small datasets [5], [8], [18]. Studies on paddy leaf disease detection demonstrate that models like Inception-based architectures can achieve classification accuracies above 90% [12].

Despite these advancements, a significant gap remains in transitioning models from controlled environments to real-world agricultural settings. Many existing models suffer from high computational complexity and latency, making them unsuitable for deployment on web or mobile platforms. Additionally, most models are trained on images with uniform backgrounds, limiting their performance under real-world conditions such as varying lighting, occlusion, and environmental noise. To address these challenges, this work incorporates data augmentation techniques, including image flipping and rotation, to enhance model generalization capability [6], [15].

C. Socio-Technical Integration and Agricultural Policy

The effectiveness of technological solutions in agriculture depends not only on accuracy but also on accessibility and usability. In India, several government initiatives aim to support farmers through financial assistance and digital market integration. However, studies indicate a significant awareness gap among farmers regarding these programs [13], [14].

Furthermore, existing agricultural systems such as weather forecasting tools, disease diagnostic platforms, and digital marketplaces operate in isolation, leading to fragmented user experiences. This fragmentation increases cognitive load and reduces the adoption of digital farming practices. Research on digital marketplaces highlights their potential to improve supply chain efficiency and farmer profitability, yet integration with advisory systems remains limited [17].

D. Identified Research Gaps

Based on the literature review, several critical gaps have been identified:

- Functionality Fragmentation: Existing systems fail to integrate AI-based diagnostics, advisory services, and marketplace functionalities into a unified platform.
- Lack of Conversational Support: Most systems provide only classification outputs without enabling interactive query-based assistance for farmers.

- Deployment Constraints: Many state-of-the-art models require high computational resources, limiting their usability in real-time web-based environments.

To address these limitations, this paper proposes an integrated web-based framework that combines a Sequential Convolutional Neural Network (CNN) for disease diagnosis [11], a Generative AI-based assistant for decision support, and a localized marketplace module for connecting farmers with relevant service providers.

III. PROPOSED METHODOLOGY

The technical framework of this research is centered on a high-precision diagnostic engine optimized for a subset of economically significant crops. The following sections detail the data engineering, architectural parameters, and training protocols employed.

A. Targeted Crop Selection and Dataset Partitioning

The base model is designed for multi-class classification, but this research focuses exclusively on improving the level of accuracy in diagnosing five main species of crops (Tomatoes, Potatoes, Corns, Grapes, and Bell Peppers) that are very vulnerable to both fungal and bacterial infections based on the conditions found in the agricultural world. The dataset used to create this model is comprised of some 54303 high resolution images contributed to the PlantVillage Image Database. In order to produce a statistically valid result, the data was divided into three separate sets.

- 80% of the data will be composed of 43442 images that can be used to train the model and adjust weightings to optimize classification;
- 10% of the data is used to tune different hyperparameters using an additional 5430 images for each species
- 10% of the data will be reserved for the final accuracy evaluation and consist of 5431 images associated with each species.

B. Image Preprocessing and Feature Enhancement

The raw image data went through several pre-processing stages to be made uniform and speed up the model's convergence:

- Dimensionality Standardization: The images were resized to 128 x 128 pixels, thereby balancing the trade-offs between keeping enough spatial details and being computationally efficient.
- Normalization: To yield pixel values between 0 and 1, images had their pixel values divided by 255.0 to centre their data and provide for more efficient and faster gradient descent.
- Real-time augmentation: In order to more accurately depict the variability that may exist in real-world environmental conditions, the model uses both RandomFlip (horizontal & vertical) and RandomRotation (0.2) layers to create artificial variability and prevent it from memorizing training angles, thus improving the model's performance on noisy captures taken from the real world.

C. CNN Architectural Configuration

The diagnostic tool is created using a custom sequential deep CNN architecture. The hierarchical extraction of features occurs through layers of abstraction as shown in the following Figure 2:

- Convolutional Layers: Three main 2D Convolutional stages were used to construct this architecture. First stage uses 32 filters, second stage 64 filters and the third stage 128 filters with a 3x3 kernel size so pattern features (leaf spots, chlorosis and necrotic lesions) can be recognised by the model because of their proximity to each other when using spatially local processes.
- Non Linear Activation: Each of the convolutional layers followed by Rectified Linear Unit (ReLU) $f(x)=\max(0,x)$ to allow for nonlinear complex features in the source images.
- Spatial Downsampling: Using a max-pooling layer following each convolutional stage with a 2x2 window reduces both parameter counts and provides a level of translation invariance such that the model will identify the disease regardless of position within the image frames.
- Global Classification: The final representations of the feature maps are single vectors created using a Flattening layer being entered into a Dense (Fully Connected) Layer containing 128 Neurons. A Softmax Layer provides the final output & serves as the probability distribution over the 38 pathology classes being considered.

D. Optimization and Training Protocol

The model utilized the Adam optimizer to compile it. The learning rate for each weight is adjusted from the first and second moment of the gradients. The objective loss function for the model was categorical cross-entropy, which minimizes the divergence between the predicted and actual probability distributions. The training for the model was conducted using 10 epochs and a batch size of 8.

The model achieved a training accuracy of 98.30% and a validation accuracy of 90.12%. These results indicate that the streamlined Sequential architecture was highly effective in detecting localized crop disease without the burden of using large pre-trained models.

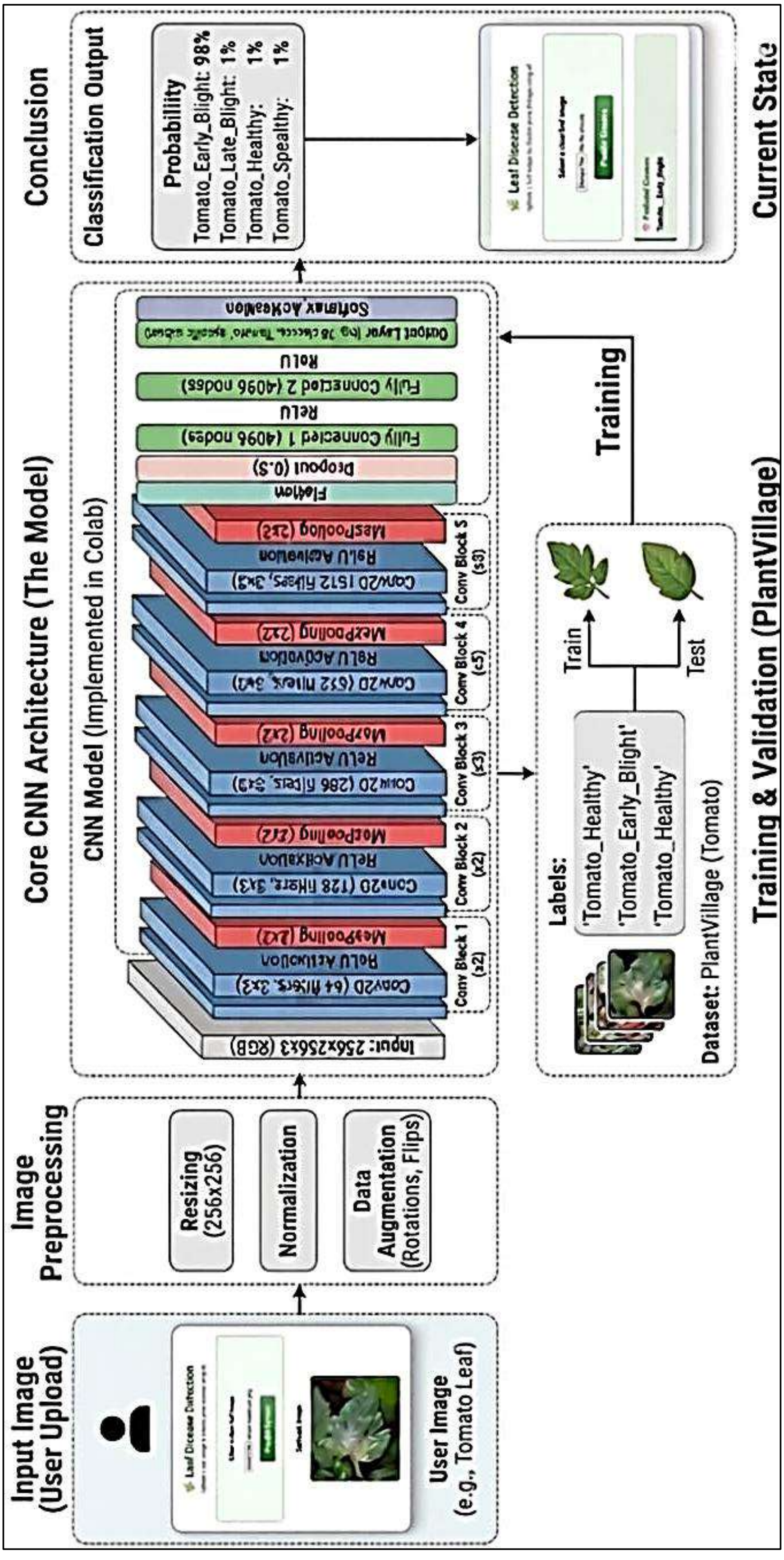

Figure 2: Sequential CNN Architecture for multi-class plant pathology classification

IV. RESULTS AND DISCUSSIONS

This section presents the experimental evaluation of the proposed CNN-based diagnostic engine and the functional validation of the integrated agricultural platform.

A. Experimental Setup and Evaluation Metrics

The model trained in a high-performance computing space with TensorFlow/Keras framework using metrics to assess the models ability to diagnose accurately. The two measures selected to evaluate the models performance was accuracy and categorical cross-entropy loss respectively. Accuracy measures the ratio of the correct identification of a particular disease by the model, while categorical cross-entropy loss measures how different the probability of the disease predicted by the model are from the actual disease that exists.

B. Model Training and Convergence Analysis

The model underwent 10 epochs of training to ensure the optimized weight convergences did not fall victim to oversaturation. Training results show that there were consistent trends of improvement throughout each of the respective phase sections (shown below in Figure 3 & Figure 4):

- Accuracy measure trends – The model started with a relative accuracy that was quickly converged to at epoch 10, whereby the training accuracy level was 98.30% and the validation accuracy was stable at a value of 90.12%. The difference in both the trained (approx. 8.18%) vs. validated accuracies reflects there being a very marginal sign of overfitting associated with unseen data.
- Loss measure optimization - The loss metric produced through categorical cross-entropy averaged very high at the beginning but then sharply declined through each epoch wherein eventually reaching training loss of 0.0537 and validation loss of 0.0770 at the aforementioned epoch 10. The smoothness of the cross-entropy loss sequence demonstrates that the Adam Optimizer has successfully traversed through the gradient surface and located stable local maxima along its gradient path.

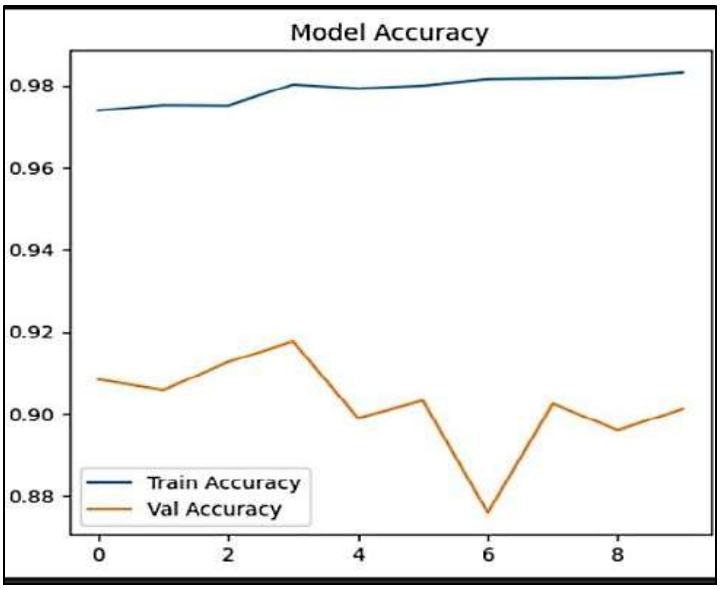

Figure 3: Training and Validation Accuracy versus number of epochs for the multi-crop diagnostic model

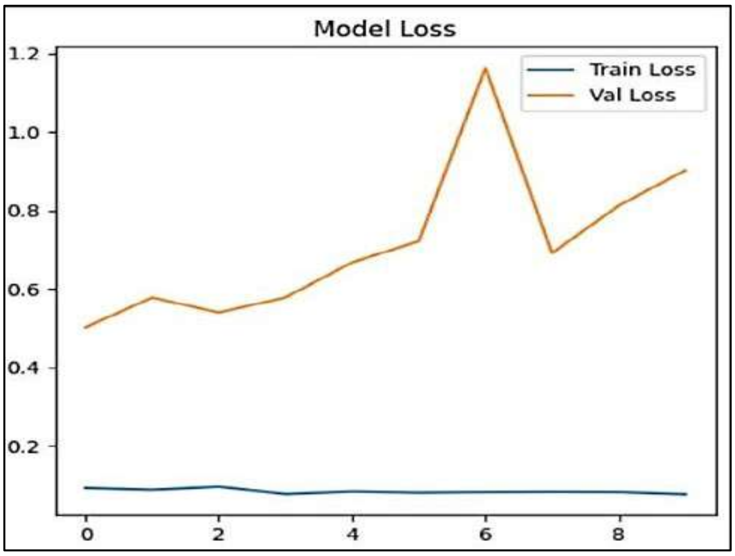

Figure 4: Categorical Cross-entropy Loss convergence for the Sequential CNN architecture

C. Performance on Target Crops

With regard to the diagnostic engine, we saw that the model produced results characterised by extremely high levels of accuracy over the five principal food crops (Tomato, Potato, Corn, Grape, Bell Pepper). The model demonstrated excellent discrimination ability with respect to the visually similar maladies of "Early and Late Blight" on Tomato and Potato leaves by also using 3 x 3 convolutional kernels able to accurately identify the necrotic pattern and chlorotic halo specific to these diseases.

Table 1: CNN Architecture Details

Layer	Output Shape	Parameters	Purpose
Input	(128,128,3)	0	Standard RGB Image Input
Conv2D	(126,126,32)	896	Edge and Texture Detection
MaxPooling2D	(63,63,32)	0	Spatial Reduction
Conv2D_1	(61,61,64)	18496	Feature Extraction
MaxPooling2D_1	(30,30,64)	0	Downsampling
Conv2D_2	(28,28,128)	73856	Pattern Recognition
MaxPooling2D_2	(14,14,128)	0	Feature Pooling
Flatten	(25088)	0	Vector Conversion
Dense	(128)	3211392	Classification Layer

In the above Table 1 presents the detailed architecture of the proposed CNN model, including layer types, output shapes, and their respective functions in feature extraction and classification.

D. Discussion of Integrated Services

In addition to diagnostic accuracy, the capability of the system to successfully integrate with the web in real time has been demonstrated through web-based performance testing as follows:

- The sequential architecture of the system facilitated the production of diagnostic results at response latencies below 200 ms/image, thus allowing for real-time deployment over the web.
- The use of a generative AI-based advisory agent has enabled an LLM to interpret CNN outputs and deliver practical action steps (e.g., fungicide recommendations for "Potato Early Blight") via a conversational interface.
- Testing completed on the Government Scheme and Marketplace modules indicated that the use of a single window interface decreased the number of steps necessary for farmers to go from diagnosis to taking administrative or commercial actions.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

A digital ecosystem for agriculture has been built that offers a user-friendly interface and intelligent backend services. The system develops a CNN specifically for five different crops producing training accuracy of 98.3% and validation accuracy of 90.12%. The CNN is capable of detecting leaves of plants in real-time. The system uses Firebase for secure authentication and provides a cloud-based storage solution to manage crops, journals, and online marketplaces. In conclusion, the results illustrate how deep learning techniques can be effectively utilized to provide timely and actionable information to farmers to support precision agriculture. Future research will involve validating the model in various field conditions while expanding the dataset to enhance the flexibility and scalability of the product.

B. Future Scope

The technology behind the platform has been designed with scalability in mind and can accommodate several different ways to incorporate future advances in technology. The key area for expansion will be to include IoT (Internet of Things) hardware, such that real-time soil and moisture sensors will provide continuous streams of data to your user dashboard for automated irrigation alerts. In order to ensure equitable access across all users, the platform will be upgraded to support multiple languages, such as Malayalam, which will be integrated into AgriBot's NLP (Natural Language Processing) model to better accommodate its local market users. Lastly, future versions of the platform will incorporate a payment gateway that is connected to UPI (Unified Payments Interface) to allow for seamless transactions between the marketplace and the end user. Push notifications will also be sent to notify end users of significant weather alerts and diseases, as such, the overall architecture of the platform will develop into a complete "Smart Agriculture" ecosystem across the global community.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] W. Chen, L. Zheng, and J. Xiong, "Algorithm for crop disease detection based on channel attention mechanism and lightweight up-sampling operator," *IEEE Access*, vol. 12, pp. 103582–103595, 2024. Available from: https://doi.org/10.1109/ACCESS.2024.3439410

[2] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, art. 1419, Sep. 2016. Available from: https://doi.org/10.3389/fpls.2016.01419

[3] Madhurya and E. A. Jubilson, "YR2S: Efficient deep learning technique for detecting and classifying plant leaf diseases,"

IEEE Access, vol. 11, pp. 125698–125712, 2023. Available from: https://ieeexplore.ieee.org/abstract/document/10360826

[4] N. Poduval *et al.*, "Plant disease detection using convolutional neural networks," *International Journal of Engineering Research & Technology (IJERT)*, vol. 13, no. 02, Feb. 2024. Available from: http://www.it.griet.ac.in/pdfs/journals19-20/SJ_4_19.pdf

[5] Balafas, E. Karantoumanis, M. Louta, and N. Ploskas, "Machine learning and deep learning for plant disease classification and detection," *IEEE Access*, vol. 11, pp. 115352–115389, 2023. Available from: https://ieeexplore.ieee.org/abstract/document/10286031

[6] M. S. Krishna *et al.*, "Plant leaf disease detection using deep learning: A multi-dataset approach," *Multidisciplinary Scientific Journal*, vol. 8, no. 1, art. 4, 2025. Available from: https://doi.org/10.3390/j8010004

[7] S. M. N. Dr., R. B. Nisa, M. R. Muktha, and D. Nayana, "Leaf disease detection using convolutional neural network," *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 12, no. 5, pp. 3345–3352, May 2024. Available from: https://doi.org/10.21203/rs.3.rs-7913477/v1

[8] K. Kaur and K. Bansal, "Enhancing plant disease detection using advanced deep learning models," *Indian Journal of Science and Technology*, vol. 17, no. 17, pp. 1755–1766, 2024. Available from: https://doi.org/10.17485/IJST/v17i17.536

[9] R. Jayamma, R. H. Chandrika, and C. D. Durga, "A comparative analysis of CNN models in deep learning for leaf disease detection," *International Journal for Multidisciplinary Research (IJFMR)*, 2024.

[10] Tejaswinia *et al.*, "Early disease detection in plants using CNN," *Procedia Computer Science*, vol. 235, pp. 3468–3478, 2024. Available from: https://doi.org/10.1016/j.procs.2024.04.327

[11] M. U. I. Tamim *et al.*, "InsightNet: A deep learning framework for enhanced plant disease detection and explainable insights," *Plant Direct*, accepted Apr. 17, 2025. Available from: https://doi.org/10.1002/pld3.70076

[12] Md. A. Islam *et al.*, "An automated convolutional neural network based approach for paddy leaf disease detection," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 1, 2021. Available from: https://tinyurl.com/4f7ukt3s

[13] K. K. Kumar *et al.*, "A convolutional neural network approach for rice leaf disease detection in India using deep learning," *Journal of Neonatal Surgery*, vol. 14, no. 4s, 2025. Available from: https://tinyurl.com/59frx6v2

[14] S. Kanakala and S. Ningappa, "Detection and classification of diseases in multi-crop leaves using LSTM and CNN models," *Journal of Innovative Image Processing*. Available from: https://doi.org/10.48550/arXiv.2505.00741

[15] P. S. Ghodekar *et al.*, "Plant leaf disease detection using CNN," *International Research Journal of Modernization in Engineering Technology and Science (IRJMETS)*, vol. 5, no. 4, Apr. 2023.

[16] N. Shelar *et al.*, "Plant disease detection using CNN," *ITM Web of Conferences*, vol. 44, art. 03049, 2022. Available from: https://doi.org/10.1051/itmconf/20224403049

[17] H. Guan *et al.*, "A lightweight model for efficient identification of plant diseases and pests based on deep learning," *Frontiers in Plant Science*, vol. 14, art. 1227011, Jul. 2023. Available from: https://doi.org/10.3389/fpls.2023.1227011

[18] K. Rashid and M. Bari, "A deep learning approach for plant leaf disease detection using transfer learning," *International Journal of Computer Applications*, 2020. Available from: https://ieeexplore.ieee.org/abstract/document/9331214

[19] J. A. Pandian *et al.*, "Plant disease detection using deep convolutional neural network," *Applied Sciences*, vol. 12, no. 14, art. 6982, Jul. 2022. Available from: https://doi.org/10.3390/app12146982

[20] P. S. R. Prasad, Ramya, Sahana, S. V. P. Sharadhi, and N. S. Nisarga, "Unified Smart Village Application System (USVAS): An AI-Driven Framework for Digital Rural Empowerment and Sustainable Agriculture," *International Journal of Innovative Research in Engineering and Management (IJIREM)*, vol. 12, no. 6, pp. 23–33, 2025, Available from: https://doi.org/10.55524/ijirem.2025.12.6.5