A Multi-Level AI Based Agri-Tech Solution for Precision Farming

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Abstract

India is a leading country in terms of agriculture, still it faces a lot of repercussions due to unpredictable environmental conditions, pest infestations and reliance on malpractices for fulfilling the demands of growing population. Therefore, *Kisan Kranti* was developed during the research. *Kisan Kranti* is an end-to-end agri-tech solution for Indian farmers. It aims to implant digitalization in agriculture for crop lifecycle management in four stages, namely crop selection, crop growth, crop treatment and crop marketing. Key features involving the use of artificial intelligence includes bi-lingual chatbot, 24 CNN models for crop disease detection and analytical machine learning model for analyzing real-time crop field parameters.

Keywords – CNN, ML, AI, Agriculture, Digitalization

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I. INTRODUCTION

Indian Agriculture is key pillar of nation's economy, ensuring livelihood to almost half of Indian population and ensuring food security across different regions. Even now this sector face many challenges that decrease both productivity and sustainability. Rapid population growth, unpredictable monsoons and shrinking natural resources and little to no minimal access to modern tech has increased the gap between potential and actual farm output. As India is advancing towards digitalization to become Digital India, therefore there is a need of incorporating modern technologies such as Artificial Intelligence (AI), Machine Learning (ML), internet of Things (IoT), etc. so that real-time analytics can be done on data in order to develop decisions quickly.

Many authors contributed in the agri-tech industry, including Mishra, Das, and Awtar observed that conventional farming practices are no longer viable to sustain the rising demand for food production. They called attention to AI as a practical way to modernize Indian agriculture, through precise farming techniques, data-driven decision making and real time monitoring [1]. The ongoing value of AI is evident in disease surveillance. AI driven crop disease learning models can easily identify plant diseases from input image with high precision. CNN trained on healthy and infected samples of diverse datasets successfully diagnosed conditions such as rust, mildew, and blight, enabling early detection and minimizing yield costs for Indian farms where support often arrives late, such AI based systems

can serve as a cost effective diagnostic alternative [2]. Climate vulnerability is another factor affecting the output of agriculture. Gallé and Katzenberger (2023) examined district level datasets to find how rainfall, temperature and wet days influence the kharif crop yields [3]. Their findings showed that increased rainfall and more wet days usually improves yields. While raised post monsoon temperatures can significantly reduce them. When emission were high, their projections indicated possibly yield reductions of 22% by century and especially in northern and eastern regions. The study tells that incorporating AI-based predictive models into adaptation strategies could help predict and manage these losses more effectively.

II. LITERATURE SURVEY

Recent studies have focused on practical AI and deep learning applications catering the needs of Indian agriculture. Islam *et al.* (2023) built CNN architectures for early leaf-disease detection using augmented image datasets, achieving near–state-of-the-art accuracy [4]. The another one is 2D CNN framework using active outline segmentation and Gaussian preprocessing showed better disease localization and reduced human monitoring time in field applications [5]. To address this challenge, Prince and colleagues (2024) created compact (CSXAI) based on CNN–SVM hybrid (CSXAI) that can be locally deployed and facilitate disease identification in real time with minimal computational power [6]. Dey *et al.* (2024) combined soil nutrient profiles and climate variables to design a user-friendly machine learning–based recommendation system to help farmers select crops best suited to local conditions [7].

Manjunath and Palayyan (2023) displays a hybrid group model based on three machine learning algorithms, including decision tree, XGBoost, and random forest to improve the accuracy of yield prediction across diverse Indian datasets [8]. Similarly, Das *et al.* (2023) demonstrate how yield forecasting can be scaled by combining Sentinel-1 and Sentinel-2 satellite imagery through ensemble models for the monitoring of sugarcane production [9].

Furthermore, Sridhara *et al.* (2024) developed multi-stage models for predicting sugarcane yield that incorporated crop growth stages to improve the temporal resolution in predictions [10]. Mohan *et al.* (2025) further advanced the field by integrating Explainable A.I. (XAI) tools with predictive systems of this type, permitting stakeholders to discern how the model encoded outputs and build trust in actionable recommendations driven by data [11]. Jabed *et al.* (2024) reviewed recent trends in agricultural yield prediction, emphasizing the need for a standard preprocessing protocol and feature-engineering protocols to enhance replicability across agricultural datasets [12].

III. METHODOLOGY

We have developed an end-to-end web-based digital solution for Indian farmers for crop lifecycle management. Our methodology deals with crops in 4 stages, as follows:

A. Crop Selection Phase:

In this phase, authentic information plays a vital role for a farmer for crop selection. Therefore, we have developed *"Kisan E-Mitra"*, a bi-lingual voice-enabled chatbot for providing authentic information to farmers. We have used our custom data to train the chatbot using *"Botpress"*, an open-source platform to develop AI agents. Apart from that, we have developed a crop selection page through which users can get information about feasible crops and soil based on their real-time location.

B. Crop Growth Phase:

For crop growth insights, we have developed a weather forecast page in which farmers can get information about 14-day weather forecast based on their real-time location to plan cropping. For that, we have fetched data from Open Meteo Weather API. Apart from that, we have included organic farming tutorials through which farmers can learn about sustainable farming practices.

C. Crop Disease Prediction:

We have developed 24 CNN models (on publically available dataset from Kaggle, an open-source platform), for many crops for diagnosing 100+ diseases based on uploaded image of plant. User can generate crop report based on the predicted disease to know more about disease, its precautions, natural remedies, organic solutions, medicinal treatment and additional usage. ML models can be made reliable using confidence score as a metrics to provide results, i.e., a threshold of probabilities greater than 90% can be configured for obtaining better results. Currently, due to financial limitations, we are not able to deploy the machine learning section therefore we have not yet implemented thresholding yet. But we are planning to make the ML models more reliable in real-time ML deployment.

As CNN models have some limitations, users should use them properly as per the instructions attached in the website in order to receive best results otherwise it may give false values based on poor test image. The user should not give images of anything other than selected crop category else model would not be able to give perfect results. Also, environmental conditions and system's camera may affect results due to clarity of image. Therefore, image of good quality in clear lighting should be used without any irrelevant background noises to receive proper results and farmer should still contact a practicing professional for seeking long term treatment guidance.

D. Crop Marketing:

For enhancing marketing experience, we have added an informative page about live prices of crops grown in different regions of India, whose data is fetched from API provided by Open Government Data (OGD) platform. Apart from that, we have developed a dedicated e-commerce portal (*"E-Dukaan"*) in which farmers can register themselves as sellers to sell their crops and products directly to a vast range of customers/purchasers. The backend of the software uses Json Web Token (JWT) authentication as well as Role-Based Access Control (RBAC) is implemented in order to enhance security of the website for maintaining privacy of Indian farmers. Currently payments gateway is not integrated in our website to keep it simple for the sake of Indian farmers so that cash-based method can be adopted with ease.

For overall accessibility of the website, we have integrated google translator API through which whole webpage can be translated to Hindi. We have also developed an Interactive Voice Response (IVR) feature which enable users to operate website using numbers (0-9), particularly feasible for keypad-based mobile phones. These user-friendly features are specifically built for enhancing usability of our website especially for Indian farmers so that they can derive best out of it. Video-based tutorials are also made available in the website itself for further support.

IV. RESULTS AND DISCUSSIONS
A. Performance Metrics

We have successfully developed an end-to-end website for Indian farmers for overall crop lifecycle management where a farmer can gain insights based on their location about crops, weather and soil, they can diagnose crop diseases by uploading images, generate crop report based on predicted disease and sell their crops and products to customers. The deployed preview is available at https://kisan-kranti.vercel.app as well as in **Fig. 1**. Also, the results obtained after training of 24 CNN models using MobileNetV2 Architecture for transfer learning in Convolutional Neural Networks, are listed in **Tables 1**, and **2**, with their validation scores based on Keras & Tensorflow architecture, respectively.
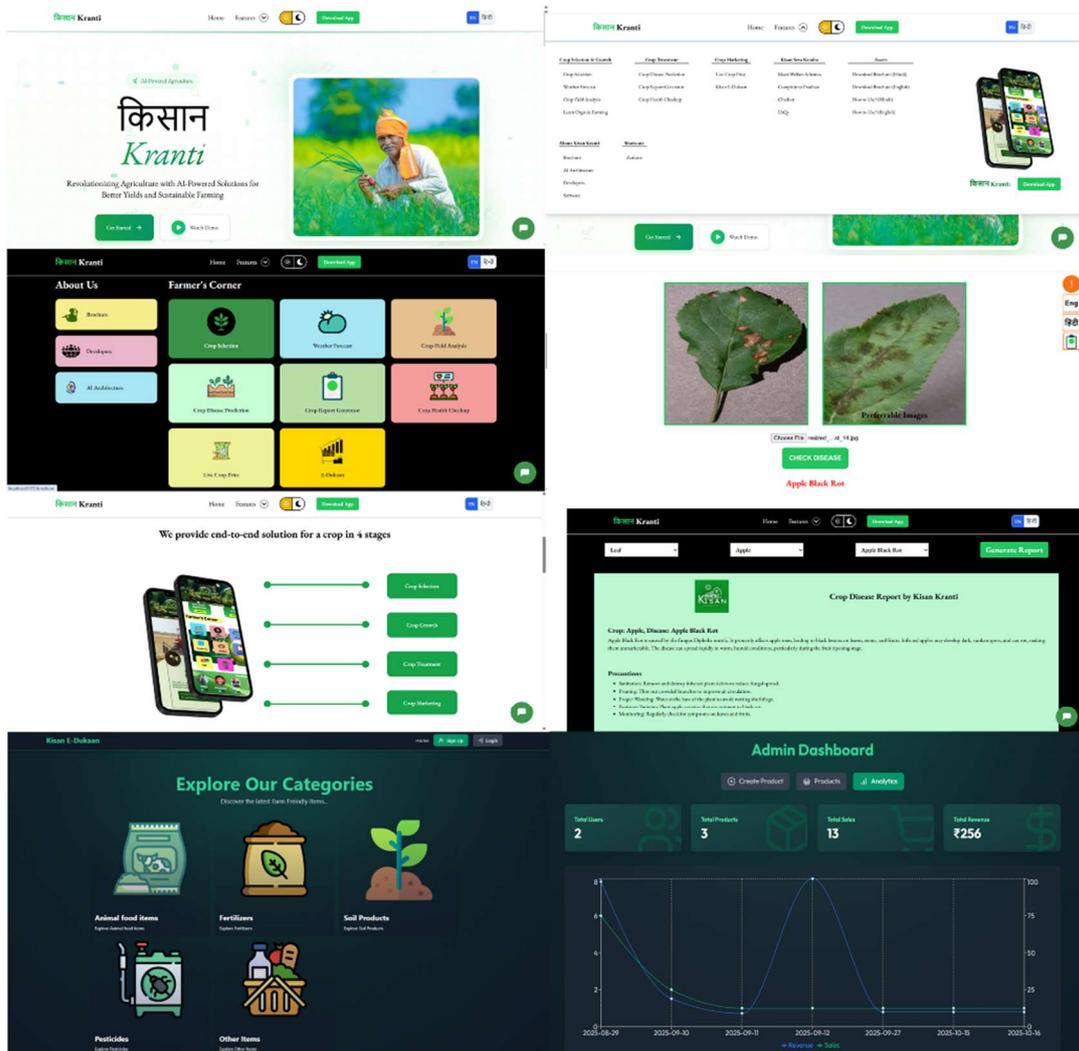
Fig. 1. Kisan Kranti Website

Table 1. CNN model training results for leaf-based diseases

S. No.	Crop	Training Metrics			Validation Metrics		
		Dataset Images	Accuracy	Loss	Dataset Images	Accuracy	Loss
1.	Apple	7771	0.9893	0.0438	1943	0.989056	0.043
2.	Banana	259	0.9953	0.8266	63	0.875	0.9545
3.	Cassava	6006	0.8924	0.627	1502	0.839	0.627
4.	Cherry	3509	0.9988	0.0279	877	1.0000	0.0276
5.	Corn	7316	0.9845	0.0653	1829	0.971272	0.1026
6.	Cucumber	3703	0.9828	0.3356	51	0.9418	0.3807
7.	Eggplant	241	0.9541	0.8242	59	0.8222	0.9442
8.	Grapes	7217	0.9881	0.1345	1805	0.97921	0.1334
9.	Money plant	12000	0.9982	0.0748	3000	0.9208	0.2454
10.	Peach	3566	0.9895	0.1299	891	0.991584	0.1111
11.	Pepper	3901	0.974	0.1416	975	0.960256	0.1599
12.	Potato	5702	0.9773	0.1571	1426	0.9745	0.146
13.	Strawberry	3598	0.9972	0.1177	900	0.998609	0.0958
14.	Sugarcane	15941	0.7789	0.6111	3985	0.8054	0.543
15.	Tomato	18345	0.7932	0.4659	4585	0.765066	0.5922
16.	Watermelon	809	0.9815	0.7884	181	0.8882	0.7884
17.	Wheat	1237	0.9571	0.7481	930	0.8098	0.9795

Table 2. CNN model training results for pest-based diseases

S. No.	Crop	Training Metrics			Validation Metrics		
		Dataset Images	Accuracy	Loss	Dataset Images	Accuracy	Loss
1.	Banana	138	1.0000	0.1441	34	0.9615	0.213
2.	Cashew	3579	0.8991	0.5094	896	0.8824	0.5264
3.	Corn	2114	0.9471	0.825	424	0.8468	0.825
4.	Cotton	856	0.8174	0.9291	727	0.7711	1.0275
5.	Eggplant	129	1.0000	0.1359	32	1.0000	0.1388
6.	Potato	1044	0.988	0.3125	235	0.9615	0.3348
7.	Wheat	662	0.9774	0.7652	171	0.8397	0.9041

B. Detailed evaluation of each CNN model
1) Leaf-based Diseases

The accuracy and loss curves for all 17 leaf-based CNN models are shown in **Fig. 2-18**, respectively which can be used to validate tabular results.
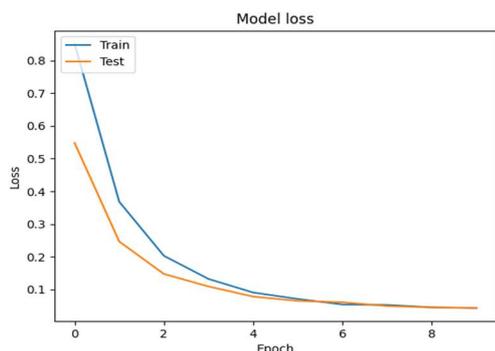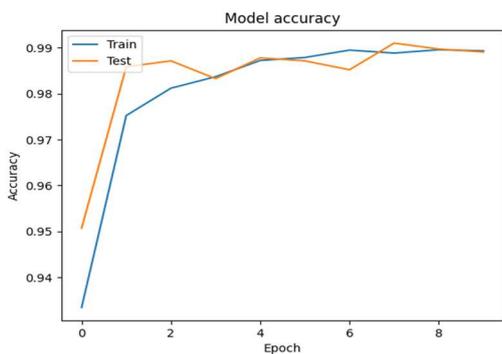
Fig.2. Apple CNN Model (Leaf-based Diseases)
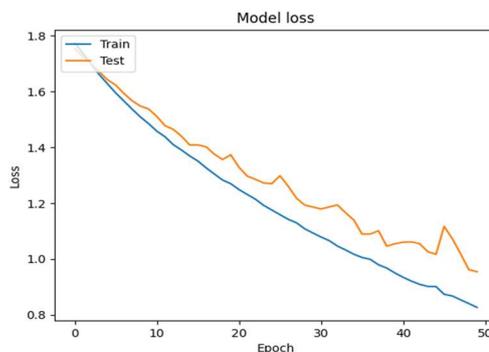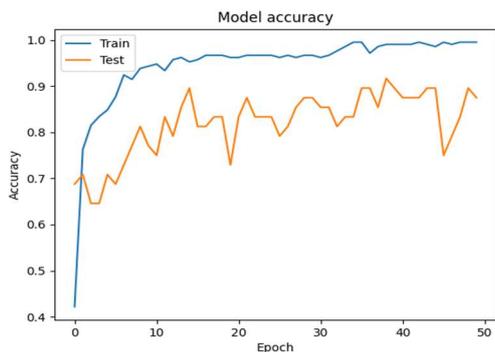
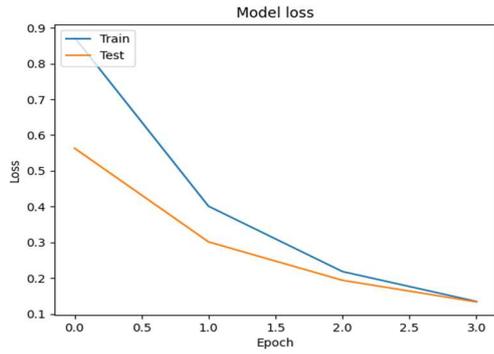**Fig.3.** Banana CNN Model (Leaf-based Diseases)
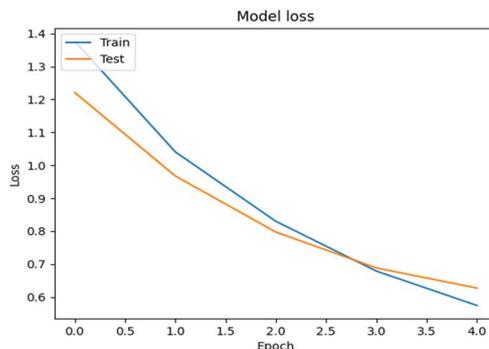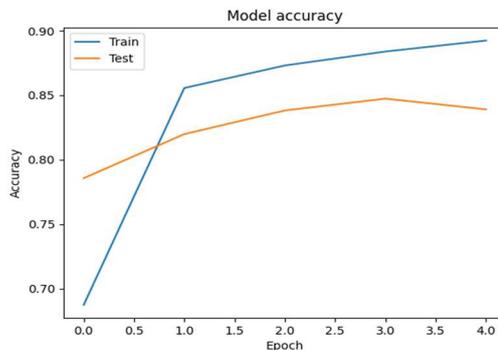
Fig.4. Cassava CNN Model (Leaf-based Diseases)
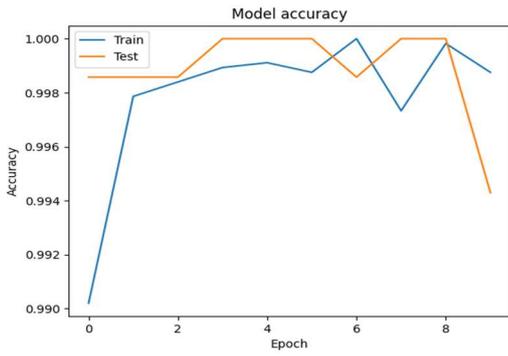
Fig.5. Cherry CNN Model (Leaf-based Diseases)
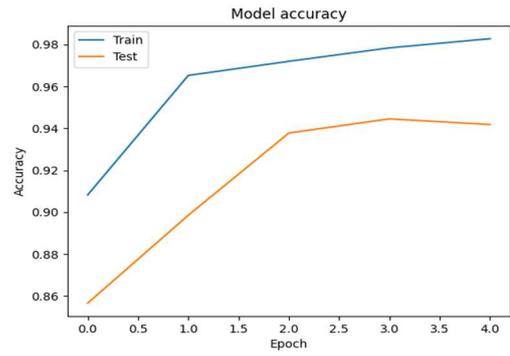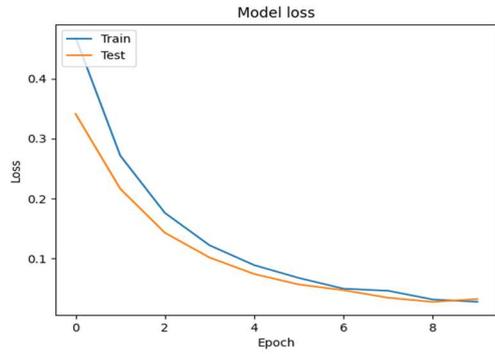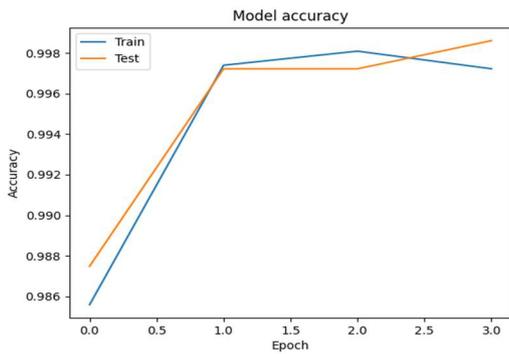

Fig.7. Cucumber CNN Model (Leaf-based Diseases)
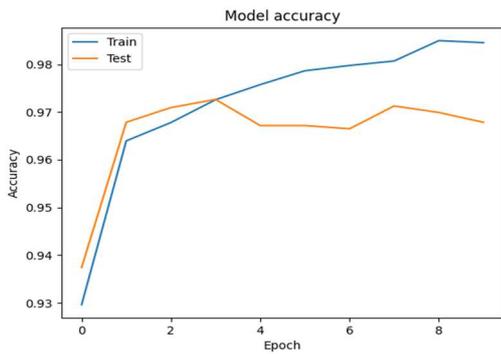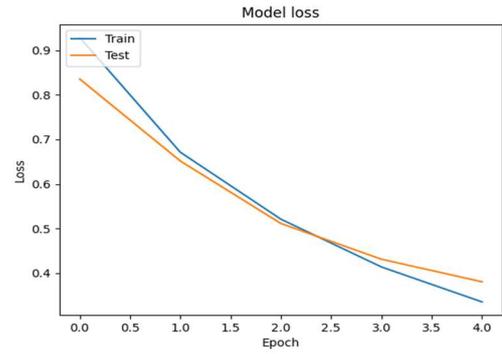
Fig.6. Corn CNN Model (Leaf-based Diseases)
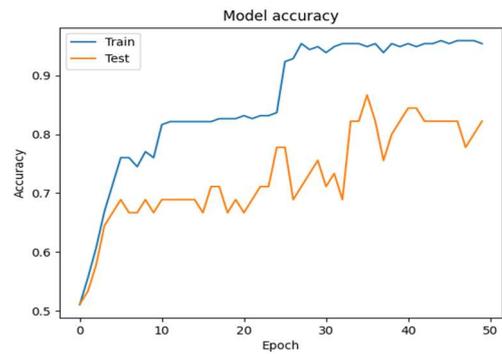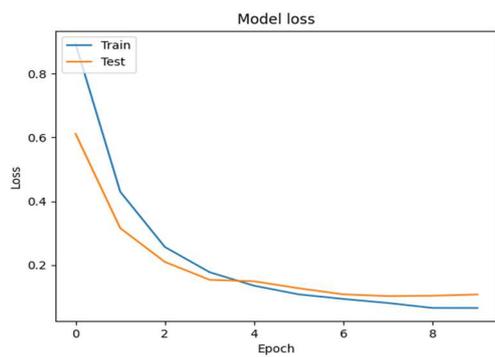
Fig.8. Eggplant CNN Model (Leaf-based Diseases)
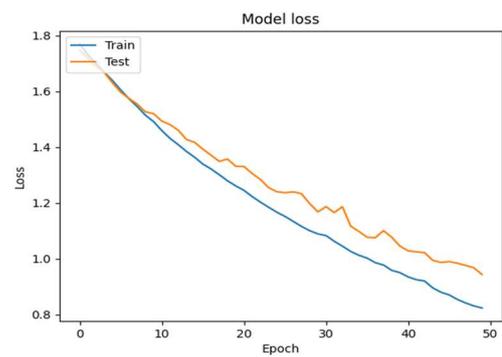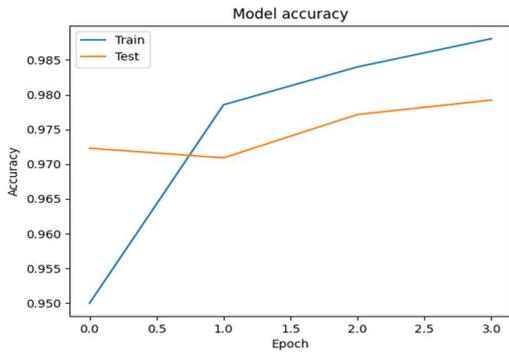
Fig.9. Grapes CNN Model (Leaf-based Diseases)
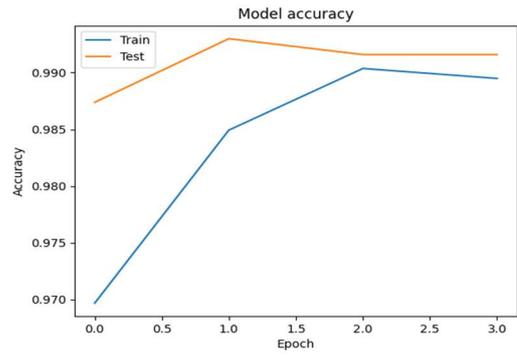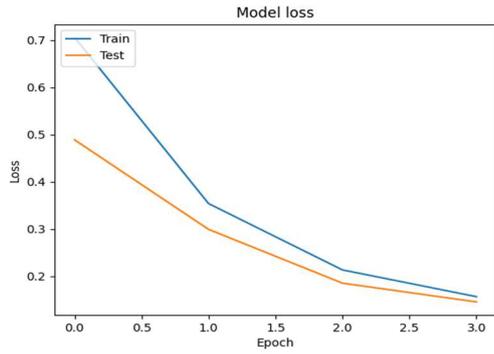
Fig.11. Peach CNN Model (Leaf-based Diseases)
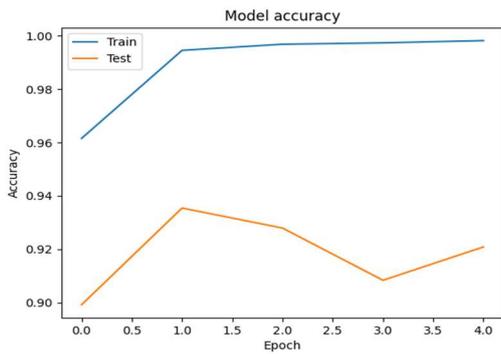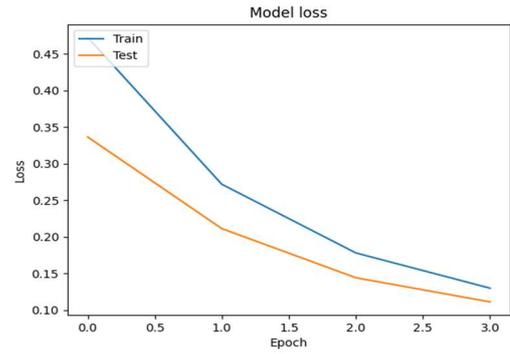
Fig.10. Money plant CNN Model (Leaf-based Diseases)
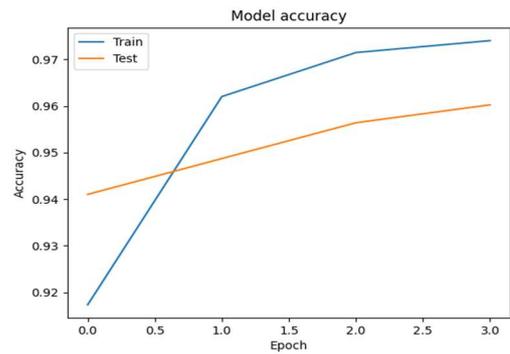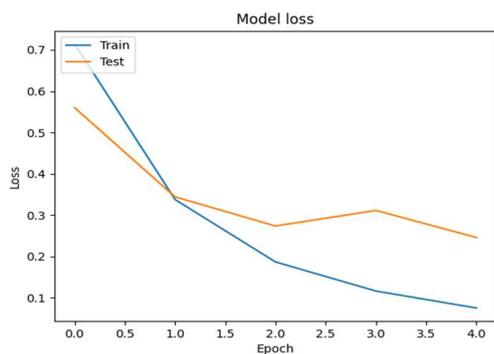
Fig.12. Pepper CNN Model (Leaf-based Diseases)
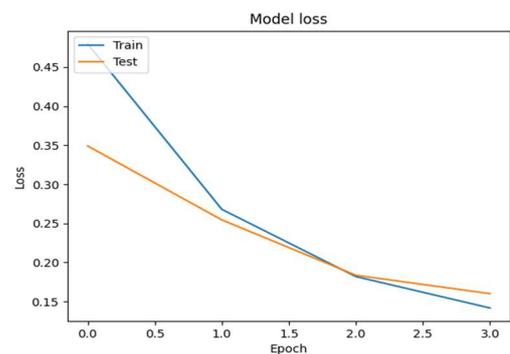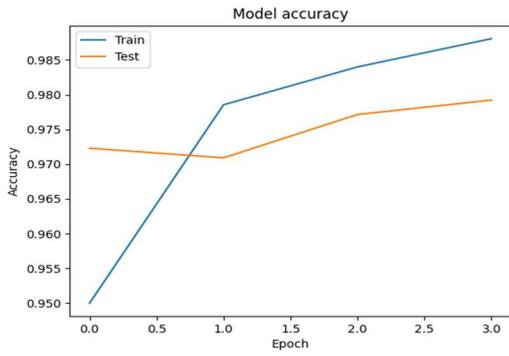
Fig.13. Potato CNN Model (Leaf-based Diseases)
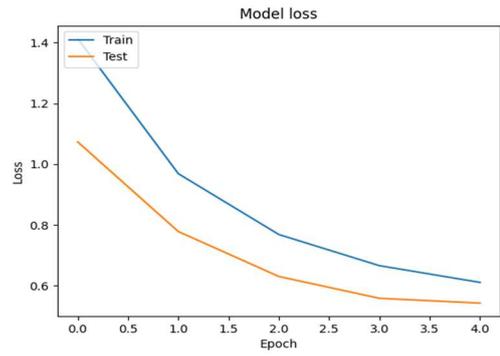
Fig.15. Sugarcane CNN Model (Leaf-based Diseases)

Fig.14. Strawberry CNN Model (Leaf-based Diseases)
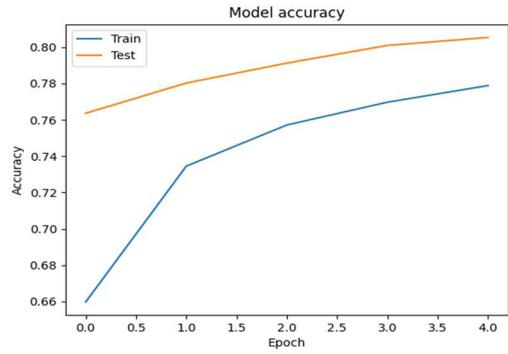
Fig.16. Tomato CNN Model (Leaf-based Diseases)

be used to validate tabular results. Poor results are obtained in Banana and Eggplant pest-based diseases due to lack of dataset. It can be further corrected using scaling of current dataset by the authors of these two datasets.
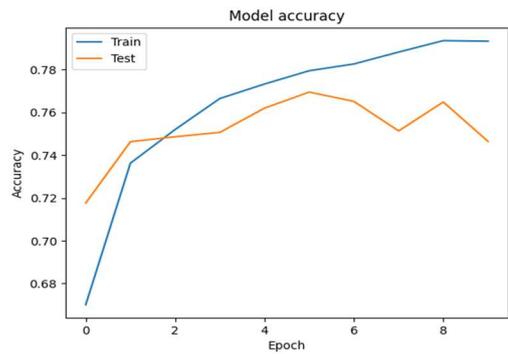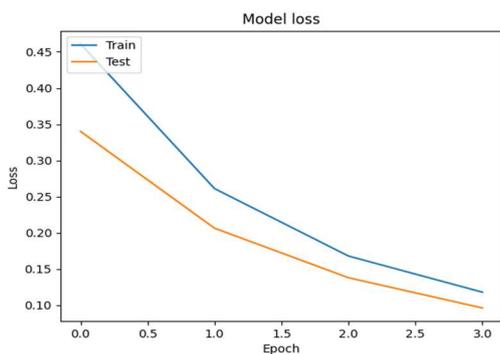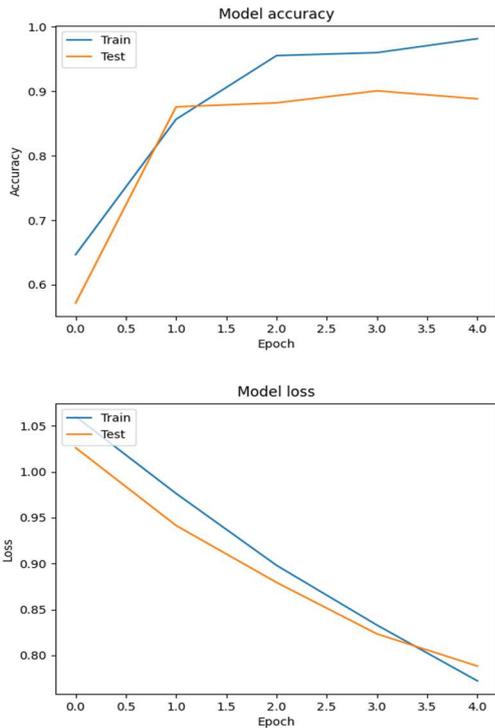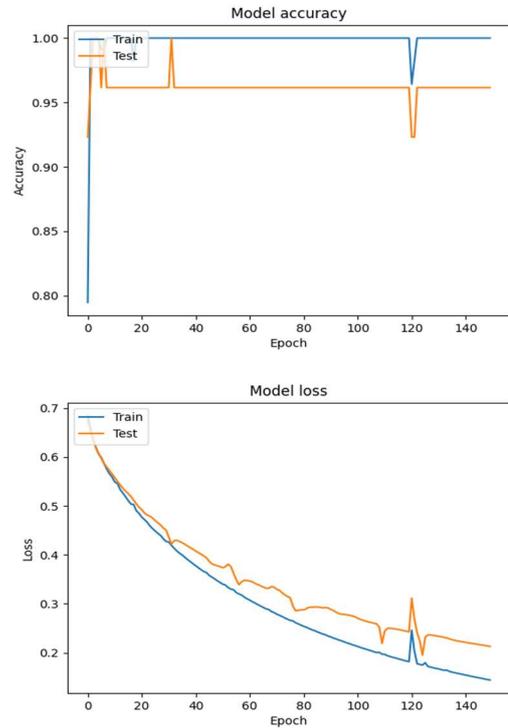

Fig.17. Watermelon CNN Model (Leaf-based Diseases)
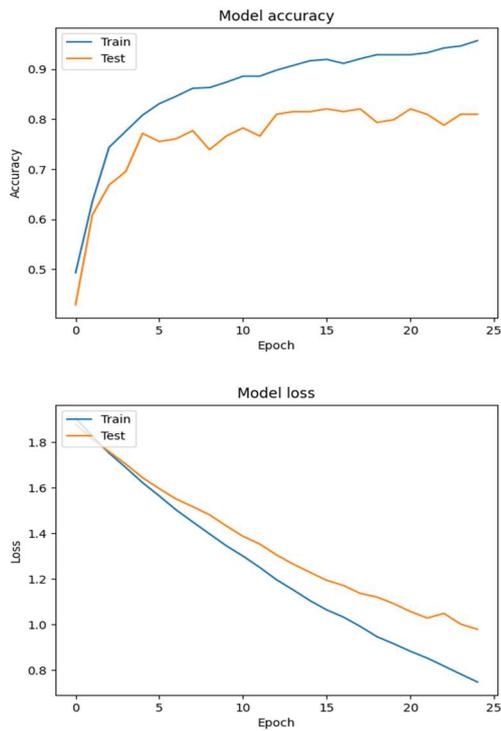
Fig.18. Wheat CNN Model (Leaf-based Diseases)

2) Pest-based Diseases

The accuracy and loss curves for all 17 leaf-based CNN models are shown in **Fig. 19-25**, respectively which can

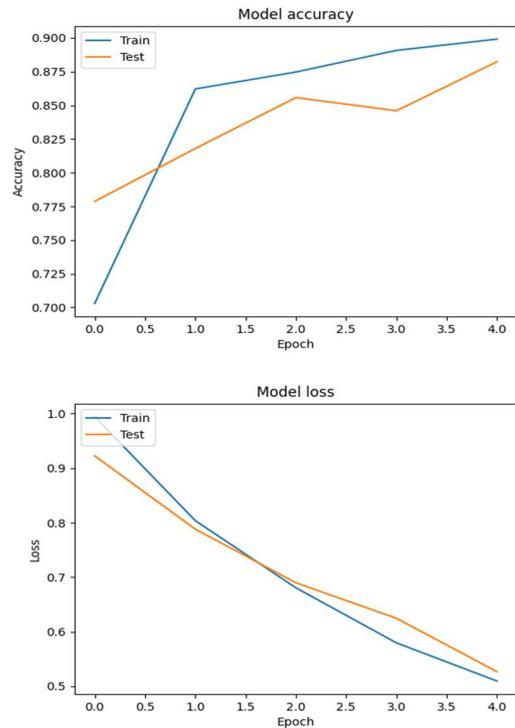**Fig. 19.** Banana CNN Model (Pest-based Diseases)

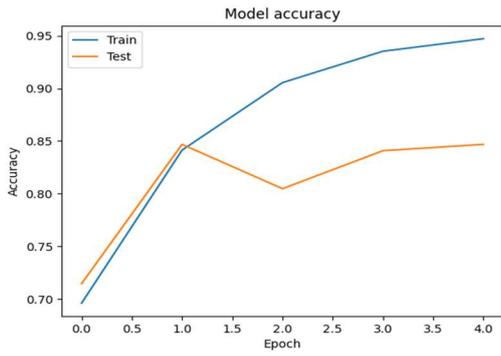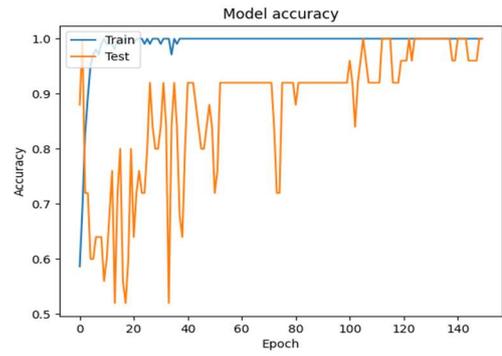**Fig. 20.** Cashew CNN Model (Pest-based Diseases)

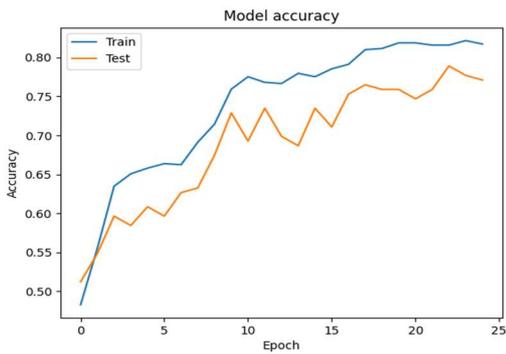**Fig. 21.** Corn CNN Model (Pest-based Diseases)
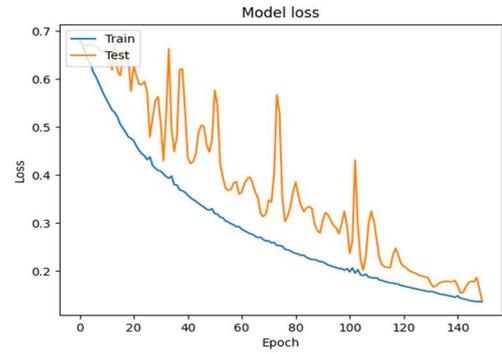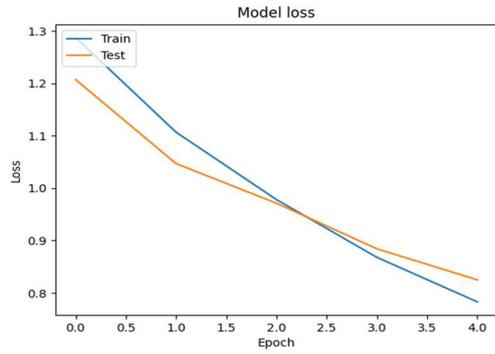

Fig. 23. Eggplant CNN Model (Pest-based Diseases)
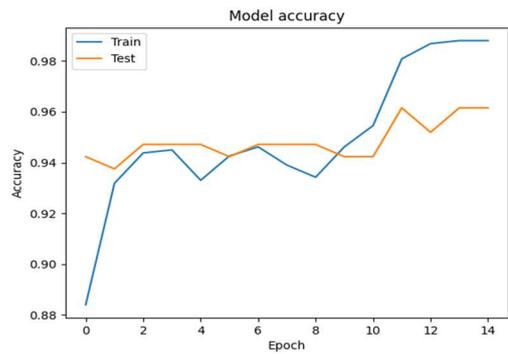

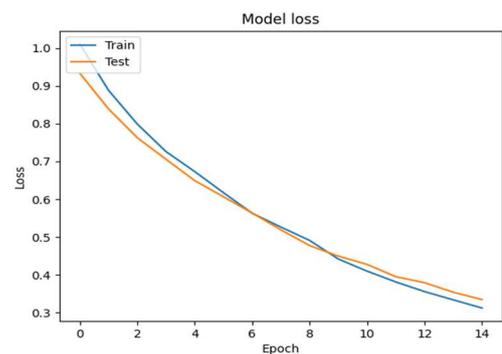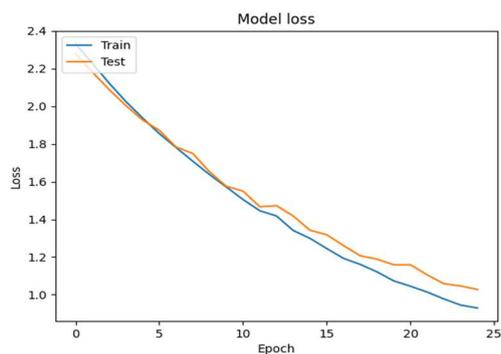**Fig. 22.** Cotton CNN Model (Pest-based Diseases)

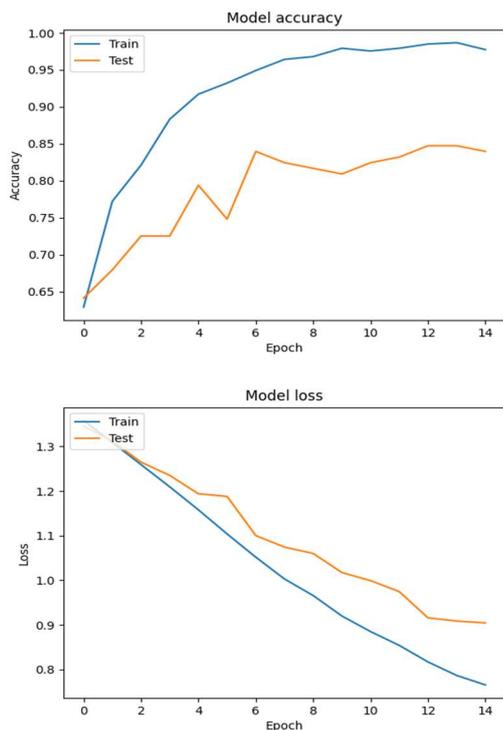**Fig. 24.** Potato CNN Model (Pest-based Diseases)

Fig. 25. Wheat CNN Model (Pest-based Diseases)

V. CONCLUSION AND FUTURE ENHANCEMENTS

Kisan Kranti has been developed as a SaaS (Software as a Service) for assisting crop lifecycle management in agriculture. It includes features for crop selection, weather and soil insights, crop field insights, organic farming tutorials, crop disease prediction, crop report generation, crop price insights, a dedicated E-Commerce platform and additional accessibility tools. It aims to assist Indian agriculture by integrating digitalization and conventional practices.

As the CNN models were developed using public datasets from Kaggle, they might have some limitations and requirements in order to get optimal results. Therefore, the image provided by the user to detect crop disease must be clear and free of background noises to achieve best results. Current version of our website does not have deployed CNN models due to financial and technological constraints. But we are planning to convert our ML models to deployable formats so that they can be accessed publically. Apart from that we are planning to apply confidence score based

thresholding to enhance security of ML models and invalid image detection for generalization.

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