

# AgroBot: A Universal AI-Based Agricultural Assistant Integrating CNN Disease Recognition and Multilingual Chatbot Support

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**Abstract.** Plant diseases significantly affect crop productivity, especially in developing regions where timely access to expert agricultural assistance is limited. Recent advancements in deep learning offer promising solutions for automated disease detection using plant leaf images. However, existing systems are generally limited by monolingual interfaces, lack of explainability, absence of administrative control, and poor field applicability.

This paper presents AgroBot, a universal AI-based agricultural assistant that integrates a custom convolutional neural network (CNN) for image-based plant disease recognition with a multilingual knowledge-driven agricultural chatbot. The system supports 38 crop-disease classes with a training image resolution of 128×128 pixels and additional text-based symptom-treatment metadata for eight languages. The CNN model achieved a 95.07% validation accuracy with a validation loss of 0.1969, demonstrating strong classification performance with minimal overfitting. The multilingual CNN-powered chatbot is driven by a structured base of knowledge based on the ideas of a JSON, which allows the domain-consistent agricultural advice.

AgroBot also supports a role-based authentication of farmers and administrators, live dataset editing, user management, and a deployment interface that is powered by Streamlit. Findings demonstrate that AgroBot is a viable, effective, and scalable solution to AI-assistance in agriculture to enhance the ease and dependability of farmers in rural areas. There are future directions that involve mobile deployment, multilingual chatbot support through speech and the possibility of implementing it with IoT crop monitoring.

**Keywords:** Artificial Intelligence · Deep Learning · CNN · Agriculture · Plant Disease Detection · Symptom Embedding · Multilingual Chatbot · Precision Farming

*(Article history: Selected papers from NIELIT's International Conference on Communication, Electronics and Digital Technologies (NICE-DT'26), 29-30Jan, 2026, Gorakhpur, India)*

## 1. Introduction

Disease of plants is an important reason that limits the production of agricultural products globally and results in high economic losses. The agricultural sector in India is very important as it contributes close to 18 percent of the GDP and employs over 50 percent of the people in the country. Nevertheless, diseases of crops still endanger the productivity of the crops which annually bring losses in billions of dollars. The significant obstacles of farmers are as follows: The failure to recognize diseases at their early stages, The unavailability of specialists in the rural areas, The language barrier, and the inability to differentiate between the symptoms of similar diseases. Disease detection through automation has thus become an important field of research in precision agriculture, enabled by developments in deep learning (DL), computer vision, and natural language processing (NLP). Conventional system of disease diagnosis needs professional expertise, of which farmers, especially in the rural areas of India, do not have.

Convolutional Neural Networks (CNNs) and DNNs have shown to be the most efficient in detecting plant diseases using leaf image [29, 17]. CNNs have allowed reaching an accuracy of over 95 percent using benchmark datasets, including 38 classes and thousands of labeled images, like PlantVillage [24, 29]. Their performance however becomes lower in real-life agriculture conditions where the images are blurred, blocked, under-lit, or complicated backgrounds [4, 11].

Most recent developments in the area of Vision Transformers (ViTs) and hybrid CNN-ViT systems have found momentum in the field of agricultural imaging. ViTs encode long-range dependencies and intricate texture distribution and achieve greater accuracy on more complicated data than CNNs [13]. The hybrid architectures based on CNN feature extraction combined with transformer-based global attention are found to be more robust to various farm conditions.

The over-dependence on images alone is also an equally critical challenge. Farmers tend to give textual descriptions of symptoms (e.g. yellow spots, brown curling leaves) rather than or in addition to photographs. The incomplete or low quality image inputs are overcome using multimodal systems that allow the combination of visual data and natural language descrip-

tion. It has been shown that in practice, image classification, combined with symptom embeddings, helps to predict better than when using only the former [15, 23].

Another important issue in India is the language accessibility. Most farmers mostly speak local languages. English only advisory systems restrict their use. Recent research and development of multilingual agricultural chatbots has demonstrated positive outcomes in terms of growth in adoption, usage and trust among rural populations [7, 10, 11]. AgroBot has been designed with the following gaps:

- Lack of multilingual services provided to different farmers.
- Absence of local instructions of treatment.
- Low interaction of chatbot-like interaction with image-based predictions.
- Lack of role-based access control on data updates.
- Systems can hardly integrate picture identification and organized knowledge bases.

AgroBot solves these problems with the help of a single platform that combines image-based diagnosis, text-based symptom interpretation, and multilingual advice based on a user-friendly interface and an administration-oriented management panel. This is a multimodal, multilingual strategy that would guarantee technical and financial soundness as well as accessibility to Indian farmers.

### a. Key Contributions of This Work

The key contributions of this research work include:

- An integrated AI-based agricultural assistant, referred to as AgroBot, which incorporates CNN-based plant disease detection and a multilingual chatbot system.
- A lightweight CNN model that can effectively classify 38 plant disease classes with a high accuracy rate of 95%.
- An integrated multilingual chatbot system that can provide effective support to farmers in disease detection.
- An effective framework that can be implemented in real-world agricultural environments.
- An exhaustive evaluation of the proposed work using metrics such as accuracy, precision, recall, F1 score, and confusion matrix.

## 2. Related Work

The research on the plant disease detection and advisory technologies is widely divided into four major sub-areas, namely, the convolutional neural network (CNN) vision models, transformer-based methods, multimodal diagnostic methods, and multilingual conversational platforms.

### a. CNN-Based Plant Disease Detection

Since the middle of the 2010s, CNNs have been the most popular method to detect plant diseases. Initial results by Mohanty et al. [29] provided valuable baselines with models like AlexNet and GoogLeNet, and subsequent works provided by Ferentinos [17] demonstrated that even more accurate results could be obtained with more complex CNN architectures. Recent work has been on lightweight and mobile-friendly CNNs, and in this case, it is possible to implement disease detection on devices, even in rural contexts with limited internet access [22, 24]. Yet, it may be claimed that CNNs can have problems with the interaction with various real-life settings despite their high efficiency. Consequently, the methods of domain adaptation and hybrid modeling have gained more significance [11, 26].

### b. Vision Transformers and Hybrid Architectures

The capability to interpret global image trends has made Vision Transformers to be highly momentum gaining. Khan et al. [2] and Yuan et al. [3] established that ViTs are more effective than CNNs when working on complicated agricultural images. Hybrid CNNViT models have also become a powerful substitute, which integrates local feature detectors with long-range attention tools [1]. These models are very effective with regard to dealing with field-collected images which are noisy.

### c. Multimodal and Symptom-Based Systems

Multimodal research corresponds to visual characteristics in combination with textual description or environmental metadata or sensor signals as a way of making predictions. A hybrid system which uses both the symptoms and images was proposed by Chen et al. [15], and the use of semantic similarity in text-based plant disease diagnosis was demonstrated by Kumar et al. [23]. Such studies confirm the Symptom Embedding Mod-ule of AgroBot as a necessary course when the quality of images is unsatisfactory.

#### d. Multilingual Chatbots for Agricultural Advisory

The adoption depends heavily on the language accessibility of language and understandability of the recommendations. Rani et al. [7] created multilingual agricultural chatbots in order to close the communication gap. Jain and Yadav [10] developed conversational systems that are tai-lored to rural India, and Srivastava and Verma [11] showed the effective-ness of NLP interfaces in farm advice. Voice-response systems also help the low-literate users [21]. AgroBot builds on this research by incorporating multilingual advisory into the same system that accomplishes the task of disease detection.

#### e. Research Gap

Although the ResNet, MobileNet, and EfficientNet models have been used in some research to identify plant diseases, these models primarily concentrate on classification tasks without incorporating interactive systems to assist farmers. Additionally, the models are computationally costly, which makes it challenging to use them in settings with limited resources. This emphasizes the need for a user-friendly, lightweight system that combines precise disease detection with easily accessible advisory support.

### 3. Dataset Overview

#### a. Image Dataset

The "New Plant Diseases Dataset," which was obtained from Kaggle, was used as the dataset for the study. This dataset consists of about 87,000 RGB images of leaves from plants, which are divided into 38 classes, healthy or diseased. This dataset provides a wide variety of plant diseases since it covers a variety of plants such as apple, grape, corn, potato, tomato, pepper, squash, etc. In order to increase the size and variability of the dataset, offline data augmentation techniques were used on the PlantVillage dataset. This dataset enables supervised learning since each image is labeled based on the type of disease or healthy condition.

The dataset is divided into training and validation sets with an 80:20 ratio for the development of the model while preserving the directory structure. The performance of the model is also evaluated by using a different test data set with 17,572 images from 38 classes.

**Table 1.** Image Dataset Summary.

| Crop   | Class Count | Examples                                                   | Type         |
|--------|-------------|------------------------------------------------------------|--------------|
| Apple  | 4           | Scab, Black Rot, Rust, Healthy                             | Fungal       |
| Potato | 3           | Early Blight, Late Blight, Healthy                         | Fungal       |
| Tomato | 10          | Septoria, Target Spot, Leaf Mold, Mosaic Virus, etc.       | Fungal/Viral |
| Corn   | 4           | Common Rust, Gray Leaf Spot, Northern Leaf Blight, Healthy | Fungal       |
| Pepper | 3           | Bacterial Spot, Healthy                                    | Bacterial    |
| Others | 14          | Grape, Strawberry, Raspberry, Soybean, Squash, Peach       | Mixed        |

#### Preprocessing

- Resize to 128×128
- Normalize pixel values to [0,1]
- Batch size: 32
- Personal folders of trains/validations/tests under TensorFlow in image\_dataset\_from directory

#### b. Multilingual Knowledge Dataset

It has a structured disease knowledge stored as a custom JSON file (symptoms\_dataset.json). To guarantee consistency between disease prediction and knowledge retrieval, every entry in the JSON dataset is directly mapped to a particular class label from the image dataset.

Each entry includes:

- unique disease ID.
- display name.
- a list of various symptoms of language.
- various language treatment guidelines.
- chatbot auto-selection confidence level.

The example languages that have been supported include English, Hindi, Urdu, Tamil, Marathi, Bengali, Telugu, Kannada. This enables the local farmers to receive local feedback.

```
{
  "disease_id": "Apple__Black_rot",
  "disease": "Apple__Black_rot",
  "symptoms": {
    "en": "Circular brown to black spots with concentric rings on leaves; rotted fruit lesions.",
    "hi": "पत्तियों पर समकेंद्रित गोल छल्लों वाले भूरा से काला चकते; फलों पर सड़न के घाव",
    "ur": "پتوں پر گول بھورا سے کالا دبیر جن میں متحدہ حلقے ہوں؛ پھلوں پر سڑنے والے زخم",
    "ta": "இலைகளில் மையவட்டவரிசை கொண்ட வட்ட வடிவமான பழுப்பு முதல் கருப்பு துளிகள்; பழங்களில் சிதைவு பாதிப்புகள்.",
    "mr": "पानांवर परिमंडताकार रिंग्स तयकरी ते काळे डाग; फळांवर सडतेले घाव.",
    "bn": "পাণ্ডায় concentric রিংস বৃত্তাকার বাগায়ী থেকে কালো দাগ; ফলার দাগে গুল্ম",
    "te": "ఆకులపై కేంద్రీకృత రింగ్స్ వృత్తాకార గల గోధుమ నుంచి నలుపు దిగులు; పండ్లపై పడిన గాయాలు.",
    "kn": "ಎಲೆಗಳಲ್ಲಿ ಪರಿಕೇಂದ್ರ ಮಂಡಲದ-ಕಪ್ಪು ಚಕ್ರಾಂಕಗಳು ಮತ್ತು ಸುತ್ತುವರಿದ ಉಳಕು; ಹಣ್ಣಿನ ಮೇಲೆ ನಾಶದ ಗುರುತುಗಳು."
  },
  "treatment": {
    "en": "Prune and destroy affected parts; maintain sanitation; fungicide sprays as recommended.",
    "hi": "प्रभावित भाग छाटकर नष्ट करें; स्वच्छता बनाए रखें; अनुशंसित कवकनाशी छिड़काव करें।",
    "ur": "متاثرہ حصوں کو کاٹ کر نیاہ کریں؛ صفائی برقرار رکھیں؛ تجویز کردہ فنگیسائیڈ چھڑکیں۔",
    "ta": "பாதிக்கப்பட்ட பகுதிகளை இழுத்து அழிக்கவும்; சுத்தத்தை பேணவும்; பரிந்துரைக்கப்பட்ட பூஞ்சை நாசினி தெளிக்கைகளைச் செய்க.",
    "mr": "प्रभावित भाग छाटून नष्ट करा; स्वच्छता राखा; शिफारस केलेले कवकनाशक वापरा.",
    "bn": "প্রভাবিত অংশ ছাটাই করে ধ্বংস করুন; স্যানিটেশন বজায় রাখুন; সুপারিশকৃত ফাঙ্গিসাইড স্প্রে করুন।",
    "te": "ప్రభావిత భాగాలను కోసి ద్వంసం చేయండి; తుదిశుభ్రతను ఉంచండి; సూచించిన ఫంగిసైడ్ రసాయనాలు వాడండి.",
    "kn": "ಪ್ರಭಾವಿತ ಭಾಗಗಳನ್ನು ಕಡಿದು ಹಾಕುವುದು; ಶುದ್ಧತೆ ಕಾಯ್ದುಕೊಳ್ಳಿ; ಶಿಫಾರಸು ಮಾಡಲಾದ ಫಂಗಿಸೈಡ್ ಸೆರ್ವಿಸ್ ಮಾಡಿ."
  },
  "confidence_threshold": 0.25
},
}
```

Fig. 1. Sample symptoms\_dataset.json for Chatbot.

## 4. Methodology

### a. System Architecture

AgroBot integrates:

1. CNN model for disease recognition.
2. Multilingual explanatory knowledge base in JSON.
3. Rule-based chatbot responses.
4. Streamlit UI for web deployment.
5. Role-based authentication using local user database.
6. Admin dashboard for dataset updates.

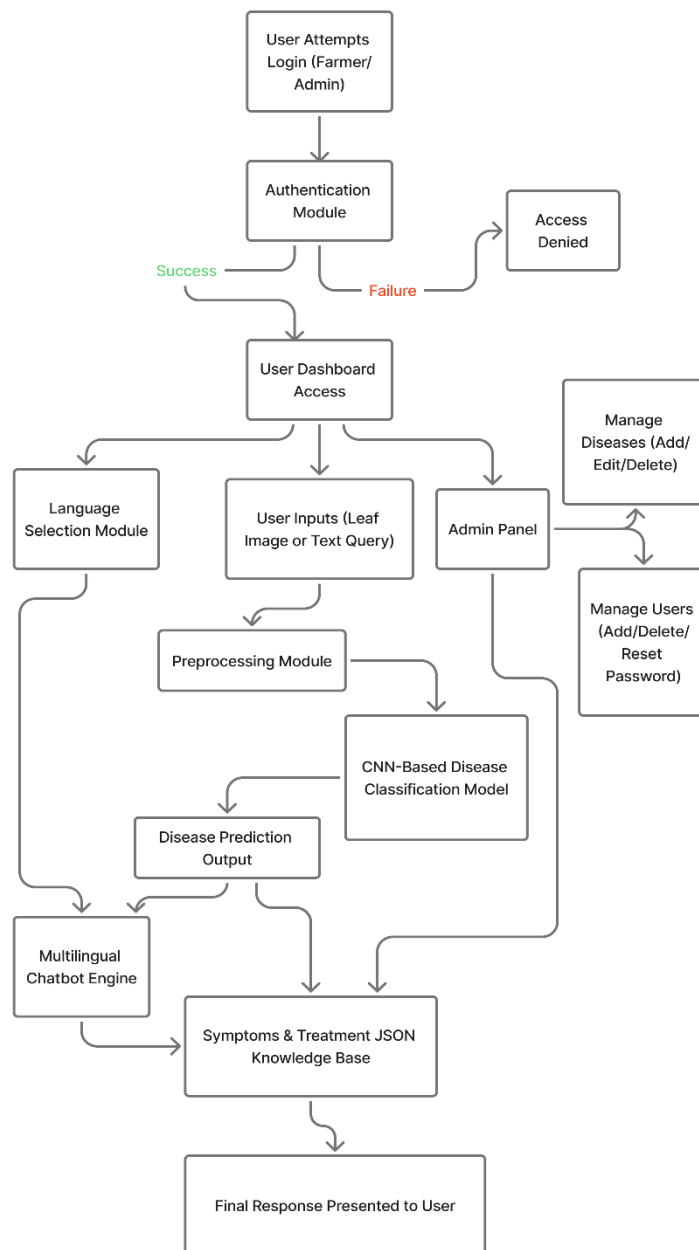


**Fig. 2.**System Flowchart Showing Authentication, Prediction, and Chatbot Integration

### b. Unique Characteristics of AgroBot

AgroBot has a unique characteristic in that it integrates:

- CNN-based visual detection.
- Knowledge extraction in many languages.
- A chatbot is an agricultural chatbot that is run on a rule basis.
- Role-based authentication.
- Real-time dataset administration.

### c. Mathematical Formulation of CNN

**Table 2.**Mathematical formulation of the proposed CNN model.

| Component                  | Mathematical Representation                                  | Description                                                                                       |
|----------------------------|--------------------------------------------------------------|---------------------------------------------------------------------------------------------------|
| Input Image                | $I \in \mathbb{R}^{(H \times W \times C)}$                   | Input image where (H), (W), and (C) represent height, width, and number of channels respectively. |
| Convolution Operation      | $F(i,j) = \sum_m \sum_n I(i+m, j+n) * K(m,n)$                | Convolution is applied using kernel (K) to generate feature map (F).                              |
| Activation Function (ReLU) | $\text{ReLU}(x) = \max(0, x)$                                | Introduces non-linearity by setting negative values to zero.                                      |
| Pooling Operation          | $P(i,j) = \max(\text{region})$                               | Reduces spatial dimensions while retaining important features (Max Pooling).                      |
| Fully Connected Layer      | —                                                            | Flattens feature maps and connects them to output neurons.                                        |
| Softmax Function           | $\text{Softmax}(z_i) = \frac{\exp(z_i)}{(\sum_j \exp(z_j))}$ | Converts output into probability distribution across classes.                                     |
| Loss Function              | $L = - \sum_i y_i \log(\hat{y}_i)$                           | Categorical cross-entropy loss for multi-class classification.                                    |

### d. CNN Model Architecture

**Table 3.**CNN Layer Summary

| Layer      | Type            | Output Shape | Parameters     |
|------------|-----------------|--------------|----------------|
| Conv2D     | 32 filters, 3×3 | 128×128×32   | 896            |
| Conv2D     | 32 filters      | 126×126×32   | 9,248          |
| MaxPooling | 2×2             | 63×63×32     | 0              |
| Conv2D     | 64 filters      | 63×63×64     | 18,496         |
| Conv2D     | 64 filters      | 61×61×64     | 36,928         |
| MaxPooling | —               | 30×30×64     | 0              |
| Conv2D     | 128 filters     | 30×30×128    | 73,856         |
| Conv2D     | 128 filters     | 28×28×128    | 147,584        |
| MaxPooling | —               | 14×14×128    | 0              |
| Dense      | 512 units       | —            | 919,040        |
| Dense      | 38 units        | —            | 19,000 approx. |

- Total parameters: 7842762 (29.92 MB)
- Trainable parameters: 7842762 (29.92 MB)
- Non-trainable parameters: 0 (0.00 Byte)

#### e. CNN Training Configuration

- Optimizer: Adam
- Loss: Categorical cross-entropy
- Epochs: 10
- Callbacks: Early stopping
- Metrics: Accuracy
- Validation Split: 80:20

Training accuracy increased from approximately 0.60 to 0.97, while validation accuracy stabilized near 0.95.

## 5. Results and Discussion

### a. CNN Classification Performance

On the independent test set of 17,572 samples:

- Overall accuracy: ~95%
- Precision: ~0.95
- Recall: ~0.95
- F1-score: ~0.95

|                                                   | precision | recall | f1-score | support |
|---------------------------------------------------|-----------|--------|----------|---------|
| Apple__Apple_scab                                 | 0.92      | 0.94   | 0.93     | 504     |
| Apple__Black_rot                                  | 0.97      | 0.99   | 0.98     | 497     |
| Apple__Cedar_apple_rust                           | 0.96      | 0.93   | 0.94     | 440     |
| Apple__healthy                                    | 0.95      | 0.89   | 0.92     | 502     |
| Blueberry__healthy                                | 0.95      | 0.96   | 0.95     | 454     |
| Cherry_(including_sour)__Powdery_mildew           | 0.98      | 0.94   | 0.96     | 421     |
| Cherry_(including_sour)__healthy                  | 0.98      | 0.95   | 0.96     | 456     |
| Corn_(maize)__Cercospora_leaf_spot Gray_leaf_spot | 0.92      | 0.91   | 0.92     | 410     |
| Corn_(maize)__Common_rust                         | 0.99      | 0.99   | 0.99     | 477     |
| Corn_(maize)__Northern_Leaf_Blight                | 0.95      | 0.93   | 0.94     | 477     |
| Corn_(maize)__healthy                             | 1.00      | 0.98   | 0.99     | 465     |
| Grape__Black_rot                                  | 0.97      | 0.97   | 0.97     | 472     |
| Grape__Esca_(Black_Measles)                       | 0.98      | 0.99   | 0.98     | 480     |
| Grape__Leaf_blight_(Isariopsis_Leaf_Spot)         | 0.99      | 0.99   | 0.99     | 430     |
| Grape__healthy                                    | 1.00      | 0.98   | 0.99     | 423     |
| Orange__Haunglongbing_(Citrus_greening)           | 0.93      | 0.99   | 0.96     | 503     |
| Peach__Bacterial_spot                             | 0.94      | 0.93   | 0.94     | 459     |
| Peach__healthy                                    | 0.99      | 0.91   | 0.95     | 432     |
| Pepper,_bell__Bacterial_spot                      | 0.93      | 0.96   | 0.95     | 478     |
| Pepper,_bell__healthy                             | 0.98      | 0.93   | 0.95     | 497     |
| Potato__Early_blight                              | 0.98      | 0.98   | 0.98     | 485     |
| Potato__Late_blight                               | 0.86      | 0.99   | 0.92     | 485     |
| Potato__healthy                                   | 0.93      | 0.97   | 0.95     | 456     |
| ...                                               |           |        |          |         |
| accuracy                                          |           |        | 0.95     | 17572   |
| macro avg                                         | 0.95      | 0.95   | 0.95     | 17572   |
| weighted avg                                      | 0.95      | 0.95   | 0.95     | 17572   |

**Fig. 3.** CNN Classification Report.

## b. Comparison with Existing Models

**Table 4.**Performance Comparison with Existing Models

| S. No. | Model        | Accuracy |
|--------|--------------|----------|
| 1      | ResNet50     | 92%      |
| 2      | MobileNet    | 91%      |
| 3      | EfficientNet | 94%      |
| 4      | Proposed CNN | 95%      |

This proposed model maintains a lower computational complexity while outperforming current methods in terms of classification accuracy.

## c. Confusion Matrix

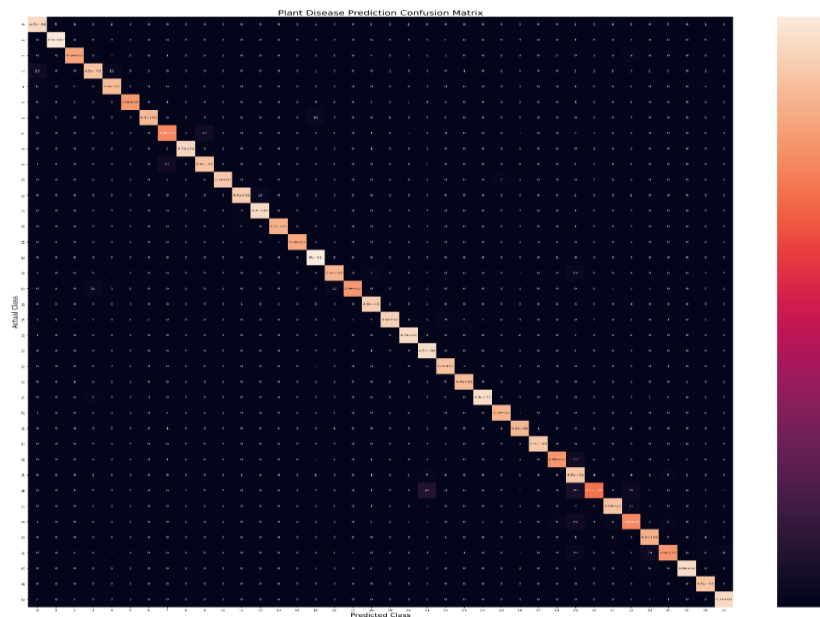


**Fig. 4.** CNN Confusion Matrix

The model displays strong diagonal dominance, indicating reliable classification across all 38 classes. The confusion matrix shows strong diagonal dominance, indicating robust class discrimination. Minor misclassifications occur among visually similar diseases such as early and late blight.

## d. Sample Inference Outputs

When tested with a healthy potato leaf:

- Predicted class: Potato\_\_\_healthy
- Confidence: 0.96

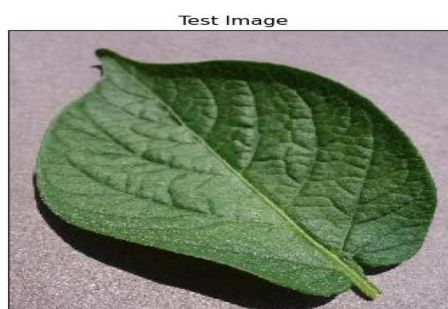


**Fig. 5.** Input/test image.



**Fig. 6.**Prediction/Output.

For a diseased potato leaf (Early Blight):

- Predicted class: Potato\_\_Early\_blight
- Confidence: 1.00

These predictions feed directly into the chatbot for contextual explanation.

#### e. CNN Accuracy vs Epochs

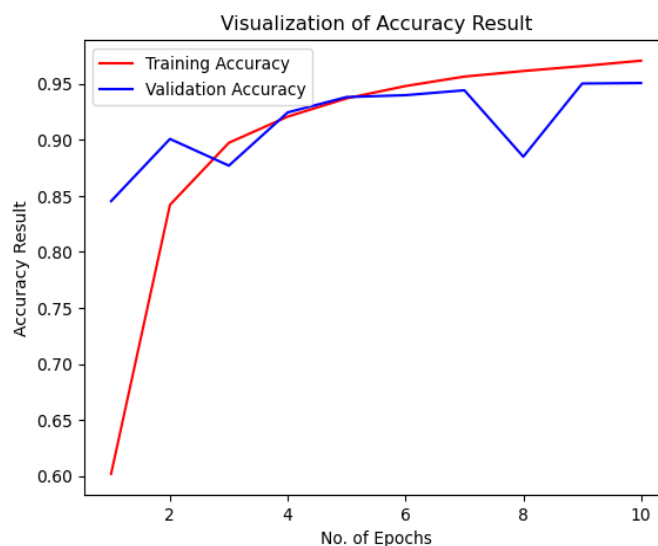


**Fig. 7.**CNN Accuracy vs Epochs plot.

#### f. Chatbot Retrieval Using Prediction

- After a successful prediction, the chatbot automatically displays the disease, symptoms and treatment text (English or the selected language).
- Example: Upload PotatoEarlyBlight4.JPG, predict Potato\_\_Early\_blight with confidence 1.00 → Chatbot populates the English/Hindi/Kannada..... entry from symptoms\_dataset.json.

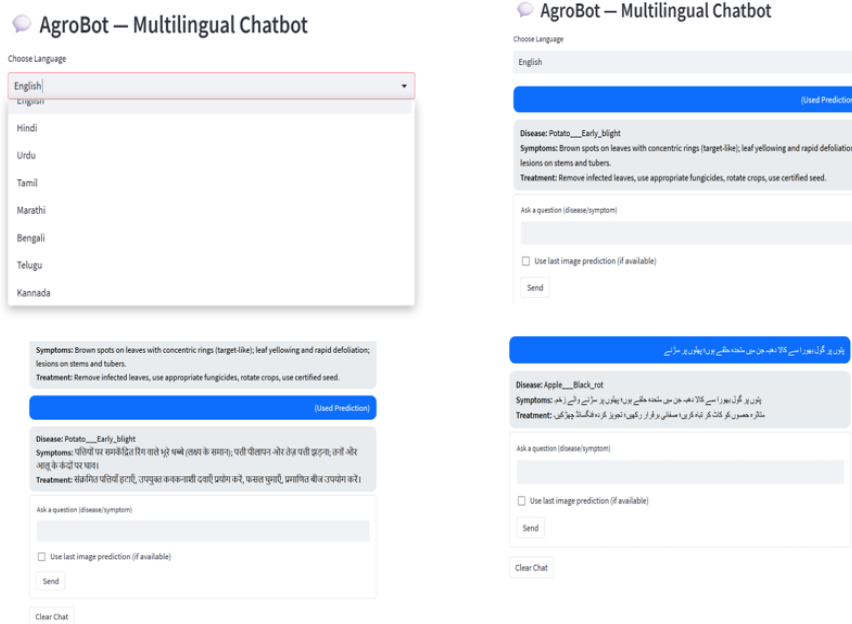


**Fig. 8.** AgroBot's Multilingual Chatbot Samples Responses.

## 6. Conclusion

This paper presented AgroBot, a universal AI-based agricultural assistant combining CNN-based plant disease recognition and multilingual chatbot guidance. The system achieves strong performance on 38 disease classes with 95% validation accuracy and supports eight languages for symptom and treatment advisory. Scalability and simple dataset updates are guaranteed by the integrated admin panel.

Future work may focus on mobile deployment, integrating multilingual chatbot support with speech capabilities, and exploring the use of IoT-based crop monitoring systems.

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