

Early Detection of Powdery Mildew in Faba Beans

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Abstract— Powdery mildew, caused by the fungal pathogen *Erysiphe*, is a widespread and economically important disease affecting broad beans (*Vicia faba*). This paper addresses the detection and treatment of powdery mildew in fava beans, covering various aspects such as symptomology, pathogen identification, disease surveillance techniques, and integrated management strategies. In this paper, we propose a mathematical model for broad bean powdery mildew detection and deep learning-based detection that improves accuracy and training efficiency. First, a conversion from the RGB format to its HSV format is performed and image segmentation is done. Then apply a random forest classifier to derive the results. The segmented leaves are then sent into a transfer learning model that has been trained on a dataset of sick leaves on a simple background. Additionally, the model is examined to identify the developmental stage of the *Erysiphe* family. By understanding the complexity of this disease, farmers and researchers can improve disease management and promote sustainable broad bean production. Therefore, for intelligent agriculture, environmental preservation, and agricultural productivity, the deep learning algorithms proposed in this article are crucial.

Index Terms— Powdery Mildew, Broad Beans, Random Forrest, *Erysiphe*, image processing.

I. INTRODUCTION

Powdery mildew, caused by the fungal organism *Erysiphe polygoni*, is one of the most commonly occurring diseases in Broad Beans.

A. Broad Bean

Broad bean (*Vicia faba*) belongs to the legume (Fabaceae) family and has an important place in both traditional and modern agriculture. Its cultivation dates back thousands of years and there is evidence that it was present in ancient civilizations such as the Egyptians, Greeks, and Romans. Botanically classified as *Dolichos lablab*, the Indian broad bean is a type of hyacinth bean and belongs to the legume family.

In India, it is also known as Avarai, Avarakkai, Sem, Sheem, and Val Papdi and in English as Lablab Beans and Indian Beans. Indian fava beans grow on thick vines with broad leaves and thrive in tropical climates.

In recent years, fava beans have attracted attention not only for their agricultural benefits but also for their nutritional value and potential health benefits.

B. Morphological Identification

On the upper side of infected leaves, there were first faint black specks that eventually turned into white patches caused by powdery mildew (Figure 1A). The spots became larger and combined with a coating of mould that was white and covered the entire leaf surface. (Fig. 1B,C). Infected leaves wilted, turned yellow, and then fell off (Figure 1C). The pods and stems got infected as the illness worsened, and eventually the damaged tissue was

covered in white powdery mildew (Figure 1B). To find out whether the leaf is diseased or healthy. The conidiophores were erect, cylindrical, $44.2\text{--}76.0 \times 8.0\text{--}10.3\text{ }\mu\text{m}$ in size, and consisted of foot cells and 1-2 short cells, forming a single conidia. Foot cells were cylindrical, straight or slightly curved and ranged in size from $22.3\text{--}30.0 \times 8.0\text{--}10.1\text{ }\mu\text{m}$ (Figure 2A). The conidia were elliptic to ovoid and $25.4\text{--}35.8 \times 13.5\text{--}19.8\text{ }\mu\text{m}$ in size (Fig. 2B). The mycelial appendages were foliate (Figure 2C). All these properties confirmed the *Erysiphe* structure.



Figure 1. Powdery mildew symptoms on the broad bean. (A) Powdery mildew blotches on a primary leaf by natural infection in glasshouse; (B) Symptoms on pods, stem, and leaves developed from pathogenicity test; (C) Symptoms on plant observed in the field



Figure 2. *Erysiphe vignae* on common bean morphology. (A) A conidiophore with a conidium attached; (B) Conidia; (C) A hyphal appressorium; (D, E) Conidia with a germ tube forming on a glass slide; (F) Conidium with a germ tube from a sick leaf; Bars = 10

C Development of Powdery Mildew

Powdery mildew clogs leaf pores, blocks light from photosynthetic cells, and reduces the plant's ability to use light as an energy source. New growth stops, old leaves fall off, and plants struggle to stay alive.

Powdery mildew tends to grow superficially or epiphytically on the surface of plants. During the growing season, hyphae are formed on both sides. Infection can also occur on stems, flowers and fruits. Specialized absorptive cells called haustoria invade plant epidermal cells to acquire nutrients. Powdery mildew produces an epiphytic mycelium known as endophysis. Conidia develop on the plant surface during the growing season.

They occur singly or in chains on the conidiophores. Conidiophores arise from epiphyte hyphae or from interstices of leaves. Powdery mildew forms ascospores at the end of the growing season in pouch-like asci surrounded by fruiting bodies called chasmoecium. Chasmothecium is usually spherical and lacks natural openings. Asci, which contain ascospores, are released when a tear occurs in the wall of the fruiting body. They can survive winter conditions as dormant mycelia within host buds and other plant tissues. These infected parts of the host can serve as primary inoculum that can induce further infection under appropriate conditions

D. Favourable Conditions and Symptoms

Fava beans can grow successfully under a variety of agro-climatic conditions, as well as with minimal effort, even in residual soil moisture, which is relatively tolerant to biotic and abiotic stresses. Powdery mildew occurs prevalently in late January-February when the plants are in the pod stage. The disease is characterized initially by the formation of white, powdery spots on the leaves, which spread toward the vines, pods and stems, covering most of the above ground as the disease progresses.

Yield loss from 100% infected crops has been estimated at 21-31% by number of pods and 26-47% by weight of pods. This pathogen causes yield losses of up to 50% and reduces pod quality. Based on the occurrence of powdery mildew, the outbreak can be divided into three broad stages.

- In the early stages, on the upper surface of the lower leaves, a white, powdery fungus grows.

- In the next stage, the fungus appears as white or greyish cottony patches on leaves, buds, and stems and spreads in a mat known as mycelium.
- At the final stage, on the mycelial mat, the fruiting body (closure) appears as a little black or brown speck. To effectively stop the spread of powdery mildew and reduce severe yield and quality losses, early detection and prompt disease control are essential.

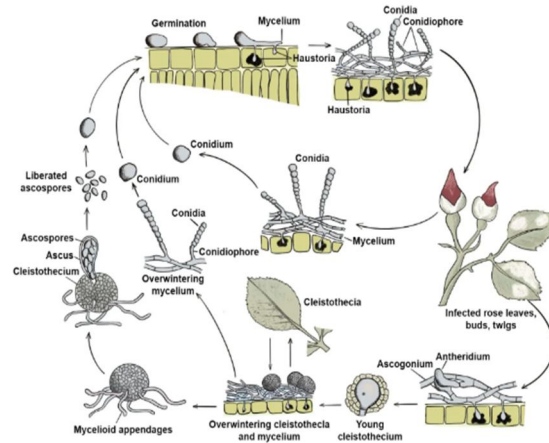


Figure 3. Life cycle of fungi *Erysiphe*

II. LITERATURE SURVEY

Visual observation is one of the most important methods for detecting powdery mildew in broad beans. Characteristic symptoms include white, powdery fungus on the undersides of leaves, stems, and pods. Researchers have studied the relationship between disease severity and symptom severity to develop a standardized disease rating scale. However, relying solely on visual observation may lead to subjective interpretation and may not be suitable for early detection of disease.

The most important biochemical methods to date include the gene chip method Ref. [2,3] and the enzyme-linked immunosorbent assay Ref. [4,5] for the detection of wheat fungi. Although the detection limits are the lowest and the detection rates are the highest, the detection processes of these methods are complex and specialized, and the long cycles and high costs make them unsuitable for large-scale fungal count detection by grain storage companies.

In addition, some research institutes have also reported many methods of fungal detection and risk prediction through detection of specific chemical constituents and fungal metabolites. Chromatography and chromatographic mass spectrometry Ref. [6] are often used to detect these characteristic substances.

However, most of these methods have serious problems: Difficult sample preparation, complicated preparation process, too many instruments and reagents. Various physical detection methods have been proposed to overcome the drawbacks inherent in biochemical detection methods. Peng Ref. [7] et al. developed his MIFI system based on radio frequency detection using Wi-Fi devices to detect wheat powdery mildew. This system allows him to achieve over 90% accuracy in detecting wheat Mold.

A study by Campagnoli et al. Ref. [8] used a commercial electronic nose with a metal-oxide-semiconductor sensor in combination with trapping and thermal desorption techniques, employing Tenax TA as an adsorbent. We identified a naturally occurring whole durum wheat grain sample. Deoxynivalenol contaminated and uncontaminated samples. These methods can be said to be physical detection methods characterized by high speed and high intelligence, but the detection accuracy is relatively poor.

Powdery mildew causes spectral changes in infected wild rockets leaves, enabling detection of the disease by proximal sensory devices and setting the stage for new disease surveillance tools. The results of this study demonstrate the potential to improve powdery mildew detection through powerful machine learning modelling based on very few bands that help efficiently identify diseased plants. However, obtaining and purchasing the equipment is very difficult Ref. [9].

Automated disease detection methods have been used for a while. The majority of the earlier methods, however, necessitate specialised setups and tools, rendering them unsuitable for autonomous detection in industrial greenhouses. In terms of algorithms, the subject of disease detection uses a variety of image processing and

learning techniques Ref. [10]. Although hyperspectral-based approaches have shown promising results, they place restrictions on the surroundings to reduce the effects of clutter. B. Restrained, plain backdrops or only depictions of plants Ref. [11].

In summary, automated disease and pest detection methods in the past required regulated and consistent environments. These requirements include a segmented view of leaves, constant camera distance, homogeneous lighting, and no obstructions or clutter. Due to the large variations in surroundings, these restrictions do not translate well into daily inspections of greenhouses.

III. PROPOSED SYSTEM

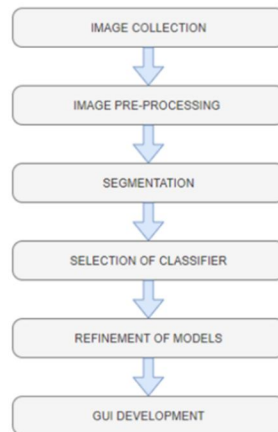


Figure 4. Workflow

The proposed study focused on early detection of fungal diseases in fava beans. This includes tasks such as image acquisition, image preprocessing, feature selection, developing methods to identify symptoms of fungal diseases in crops, and finally developing the architecture of the proposed system.

A. Image Acquisition

First, legume leaf fungal disease is analysed to identify powdery mildew growth. Additionally, images of infected plants are from reliable sources.

B. ImagePre-processing

The fundamental goal of picture pre-processing is to provide non-inherited images the options they need and to prevent undesired distortions for further processing. Here, the image is enlarged and shaped, the image's noise is eliminated, and various morphological alterations are processed to raise the image's quality. Increasing contrast is another goal of image improvement.

C. Conversion of image from BGR to HSV

HSV divides the luminance, or image intensity, from the saturation, or colour information, in contrast to RGB. This has numerous applications and is quite helpful. For instance, you would generally just apply histogram equalisation to the intensity component of a colour image and ignore the colour component altogether. Otherwise, you'll see some extremely odd colours. In computer vision, we frequently want to distinguish between colour and intensity for a variety of reasons. Enhancing resistance to light fluctuations or getting rid of shadows.

D. Image segmentation

It is a technique for breaking an image up into smaller pieces. Utilising approaches for hue estimates, segment and group photos. The fact that the leaves are green is natural and unimportant. Choose cluster photos with infected areas to extract features from.

D. Feature Extraction

A binary mask defines a region of interest in an image. Apply Global Feature Descriptors: Three feature descriptors are used to extract global features from the image.

- Colour: colour channel statistics (mean, standard deviation) and color histogram

- Format: Hu moment, Zernike moment
- Textures: Halalic Textures, Local Binary Patterns

After extracting the image features, the features are stacked using the numpy function `np.stack`.

E. Feature Scaling

Feature scaling is a technique that normalizes the independent features present in the data to a fixed range. This is done during data preprocessing to handle different sizes, values or units. If no feature scaling is performed, machine learning algorithms tend to weight large values more heavily and consider smaller values to be lower, regardless of the unity of the values. I used a min-max scaler here. This scaling puts the values between 0 and 1.

F. Modelling

This includes categorization and training. A decision tree-based supervised learning method called Random Forest. The tree's leaf nodes are made up of labelled data. The disadvantage of overfitting the training data set is overcome by random forest, which also handles categorical and numerical data. N features are chosen at random from a pool of M features in a random forest. By choosing features/attributes at random from the available features/attributes, Random Forest constructs numerous trees (N). All N trees in the forest are subjected to the input data. Each tree independently predicts outcomes from other trees. The maximum votes received for each type projected in the forest serve as the output of Random Forest's predictions.

IV. RESULTS

The colour of the leaf is retrieved from the image to execute segmentation, which is the process of separating the leaf image from the background.

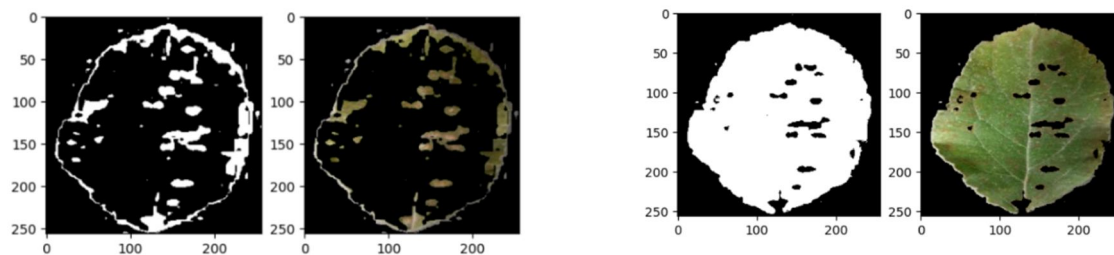


Figure 5

According to the findings, the accuracy is 97.1%, which is higher than the accuracy of the conventional approach and lessens the negative effects of illnesses on agricultural productivity while fostering the growth of sustainable agriculture. As a result, the random forest algorithm suggested in this work is crucial for environmentally friendly agriculture, agricultural production, and intelligent agriculture.

V. DISCUSSION AND CONCLUSION

In this study, we introduce a system based on a machine learning approach. In order to address the Powdery Mildew disease recognition problem in Faba Bean crop, we have used feature extraction and classification algorithm for image processing. By taking digital images of plant leaves, we can extract and classify infected areas according to the stage of development of powdery mildew.

Random Forest was used to classify the Faba bean disorders, and the relative benefits of our study were evaluated by comparing the outcomes of later similar studies. The accuracy we attained was 97.1%, which is both encouraging and positive. A very large data set of photos could still be used in future study to cover a larger range of Faba bean illness. In the future, a further focus could be on developing early warning systems that integrate weather data and disease models to predict outbreaks.

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