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Precision Agriculture for Enhanced Crop Management: Leveraging Technology in Hops Classification

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ABSTRACT

Agriculture, the foundation of civilization, supports life and industries. Growing worldwide populations and changing climates require innovative food production technologies. Precision agriculture uses technology to streamline processes, reduce resource waste, and boost yields. Advanced crop classification, especially in hops, may change this field. Manual labor and simple instruments dominated traditional agriculture. Veteran farmers used leaf shape, color, and fruiting qualities to classify crops. Although effective, this system was time-consuming, error-prone, and unsuitable for large-scale farming. Technological advances have enabled more advanced methods. Several key elements promote precision hops classification. The brewing sector, a major hops user, requires cultivars with distinct Flavors and aromas. Proper classification assures hops grown to these standards. Crop management must optimize water, nutrients, and pest control to meet sustainability goals. Improved crop classification boosts yields and market prices, helping farmers survive. Developing an advanced hops categorization system is the difficulty. This system would use advance machine learning and computer vision to distinguish hop varietals. The purpose is to enable rigorous crop management and ensure harvested hops meet brewing industry quality standards. Hops classification is a major agricultural advance. Hop plant photos are analyzed using cutting-edge technologies including machine learning algorithms and computer vision. These models, trained on large datasets, can spot small distinctions that humans cannot. The system learns to classify hop varietals with great accuracy. A more efficient and precise hop crop management system yields higher-quality hop harvests for the brewing sector. This innovative strategy boosts farmer yields and resource efficiency and assures a consistent, high-quality brewing supply chain.

Keywords: Precision agriculture, Crop classification, Hops, Machine learning, Brewing industry, Sustainability, Crop management

1. Introduction

Agriculture serves as the backbone of civilization, providing sustenance and supporting various industries. With the global population on the rise and climates undergoing changes, the need for innovative food production technologies has become increasingly evident. Precision agriculture has emerged as a solution, leveraging technology to streamline processes, minimize resource wastage, and enhance crop yields. Traditional agriculture relied heavily on manual labor and basic instruments for crop classification. Veteran farmers utilized characteristics such as leaf shape, color, and fruiting qualities to categorize crops, albeit with limitations of time consumption and error-proneness. However, technological advancements have ushered in more sophisticated methods, offering opportunities for precise crop classification and management. India's agricultural sector plays a pivotal role in the

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country's economy, employing a significant portion of the workforce and contributing substantially to the GDP. According to statistics from the Ministry of Agriculture and Farmers' Welfare, agriculture employs over 50% of the Indian workforce and accounts for around 15% of the GDP. Moreover, India is one of the largest producers of hops, an essential ingredient in the brewing industry. Hops cultivation is primarily concentrated in states like Himachal Pradesh, Uttar Pradesh, and Jammu & Kashmir. The brewing sector, which heavily relies on hops for distinct flavors and aromas, constitutes a significant market for hop producers in India. However, despite its importance, the Indian agricultural sector faces challenges such as water scarcity, soil degradation, and the need for sustainable farming practices. Precision agriculture, including advanced crop classification techniques, holds promise in addressing these challenges by optimizing resource utilization and enhancing crop yields.

In India, the adoption of precision agriculture techniques, including advanced crop classification in hops, can revolutionize the agricultural landscape. By leveraging cutting-edge technologies such as machine learning and computer vision, farmers can enhance crop management practices, optimize resource allocation, and ensure high-quality harvests. The development of an advanced hops categorization system, powered by machine learning algorithms and computer vision, can significantly benefit Indian hop farmers and the brewing industry. By enabling precise crop management and quality assurance, this innovative approach can boost farmer yields, improve resource efficiency, and contribute to a consistent supply chain for the brewing sector.

2. Literature Survey

The increase in demand for crops and food production is associated with the growth of the world population, which according to data from the Food and Agriculture Organization (FAO) of the United Nations, is currently 7.7 billion humans, projected to be 9.4 billion in 2030 and 10.1 billion in 2050, when the world population will need 70% more food, 42% more arable land and 120% more water for food-related purposes [1,2,3,4]. Since traditional outdoor agriculture does not satisfy food production, coupled with the reduction of limited agricultural land for civil works construction, an optimal solution is protected crops called greenhouses that increase the number of harvests. Better yet, when transformed to smart greenhouses using information technology and sensors, can contribute to the increase of agricultural production [5]. In relation to the technological advances of Industry 4.0, cloud computing and the IoT (Internet of Things) contribute to making traditional systems smart [6,7,8]. An example of this process is smart farming (SF) that improves productivity and reduces surplus elements used in crops [9] On the other hand, within the IoT concept, the role of wireless sensor networks (WSN) is paramount [10,11] because several IoT applications are based on wireless data transmission allowing sensor/actuator nodes to communicate with each other through a wireless network connection, even potentialized within the mMTC (massive machine-type communications) scenario of 5G [12,13,14,15].

3. Proposed Methodology

This project implements a graphical user interface (GUI) application for hop plant image classification. The project involves using machine learning techniques, specifically Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) models, to classify images of hop plants into different categories such as pests, nutrient-related issues, healthy plants, and various diseases (powdery and downy mildew) as shown in Figure 1. Here's an overview of the project:

- GUI Setup: The project uses Tkinter, a Python GUI library, to create a graphical interface. The GUI includes buttons for different functionalities and a text area to display information.

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— Dataset Handling: The application allows users to upload a dataset of hop plant images. The dataset is expected to have subdirectories corresponding to different categories of images.

— Image Processing: After uploading the dataset, the code provides functionality for image processing and normalization. This likely includes resizing images to a consistent size and converting them to a format suitable for model training.

— MLP Classifier: The project employs a Multilayer Perceptron (MLP) classifier to train a machine learning model. The MLP model is trained on features extracted from the images. The training process involves splitting the dataset into training and testing sets, evaluating accuracy, and displaying a confusion matrix.

— CNN Model: In addition to the MLP classifier, there's a Convolutional Neural Network (CNN) model. CNNs are commonly used for image classification tasks. The code defines a CNN architecture, trains the model, saves its weights and architecture, and displays the accuracy of the trained model.

— Test Image Prediction: The application allows users to upload a test image for classification using the pre-trained models (MLP and CNN). The predicted class is displayed on the image using OpenCV.

— Graphical Representation: The GUI includes a button to plot a graph showing the accuracy and loss over training iterations for the CNN model.

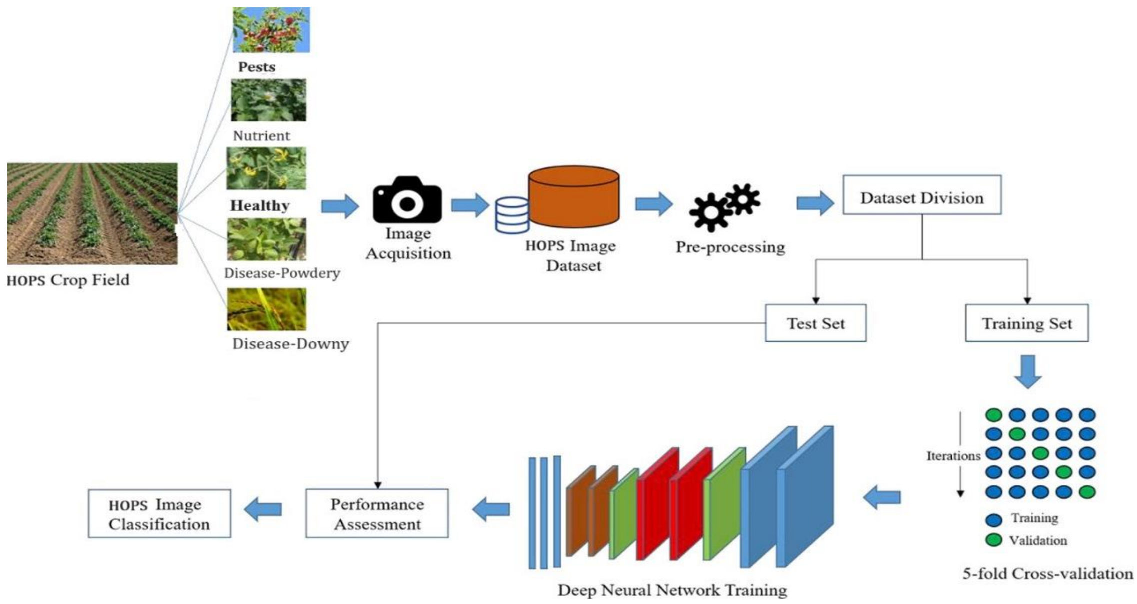

Figure 1: Proposed architecture diagram of hops classification model.

3.1 CNN

Deep neural network is gradually applied to the identification of malaria conditions. Deep neural network is designed by imitating the structure of biological neural network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network. The success of DLCNN network model also confirms the importance of

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convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis, and other fields.

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for malaria condition recognition is shown in Figure 2.

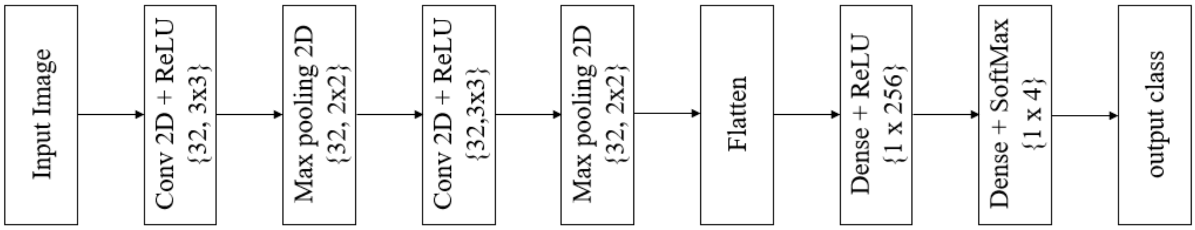

Figure 2: Proposed DLCNN

The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Convolutional neural network mainly solves the following two problems.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Image stability: Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation, and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

Convolution layer: According to the facts, training and testing of DLCNN involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU),

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max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1].

Convolution layer as depicted in Figure 3 is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F\left(k_x, k_y, d\right)$.

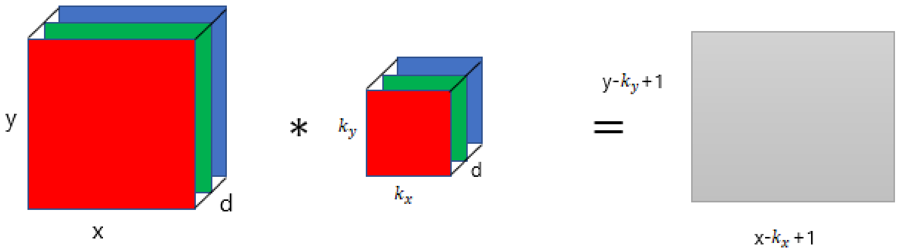
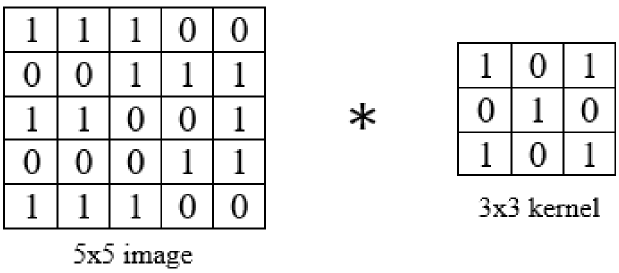
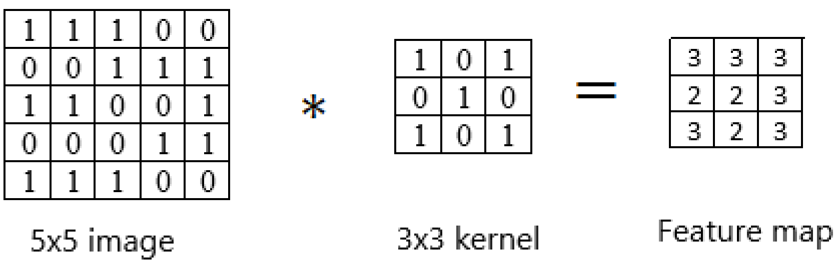


Figure 3: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), \left(y - k_y + 1\right), 1\right)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 4(a). Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values as given in Figure 4 (b).



(a)



(b)

Figure 4: Example of convolution layer process (a) an image with size $\mathbf{5} \times \mathbf{5}$ is convolving with $\mathbf{3} \times \mathbf{3}$ kernel (b) Convolved feature map

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ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

SoftMax classifier: Generally, softmax function is added at the end of the output as shown in Figure 5, since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

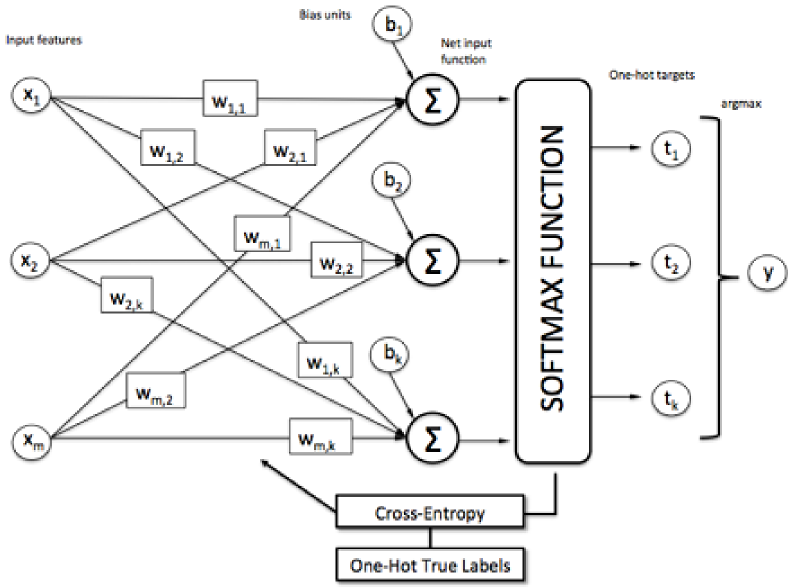

Figure 5: Malaria prediction using SoftMax classifier.

4. Results and Discussion

The results and performance of the proposed Convolutional Neural Network (CNN) architecture for hops classification are comprehensively presented through several figures and a table. Figure 6 provides a detailed summary of the proposed CNN architecture, outlining the structure and layers of the model, which include various convolutional layers, pooling layers, and fully connected layers designed to effectively extract and learn features from input data.

Figure 7 showcases the prediction results of the proposed CNN algorithm, illustrating its high accuracy and capability in correctly classifying hops samples. This visual representation likely includes

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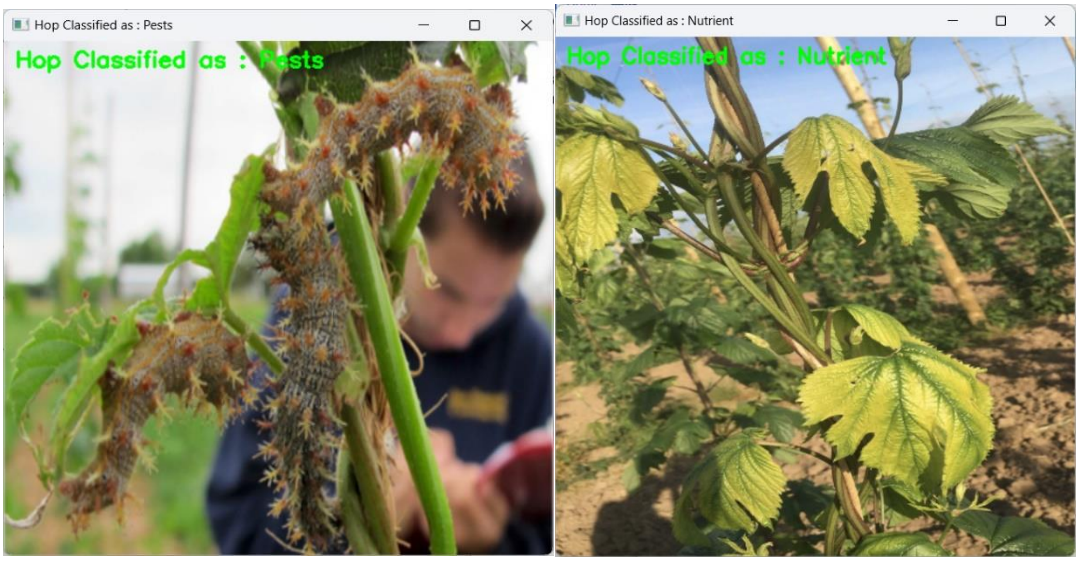
confusion matrices or sample classification outputs, demonstrating the model's effectiveness in real-world scenarios. Figure 8 presents the accuracy and loss graph for the proposed model, showing the training and validation curves over epochs. This graph highlights the model's learning process, indicating a steady improvement in accuracy and a reduction in loss, thereby confirming the robustness and efficiency of the training procedure. Additionally, Table 1 compares the performance of the Multi-Layer Perceptron (MLP) classifier with the CNN model. The table clearly shows that the CNN model significantly outperforms the MLP classifier, achieving an accuracy of 96.0% compared to the MLP's 79.7%. This substantial improvement underscores the CNN's superior ability to handle the complexity of the hops classification task, likely due to its advanced feature extraction and learning capabilities.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 29, 29, 32)        9248
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 6272)              0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               1605888
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 1285
=================================================================
Total params: 1,617,317
Trainable params: 1,617,317
Non-trainable params: 0
_________________________________________________________________
None
```

Figure 6: Model summary of proposed CNN Architecture



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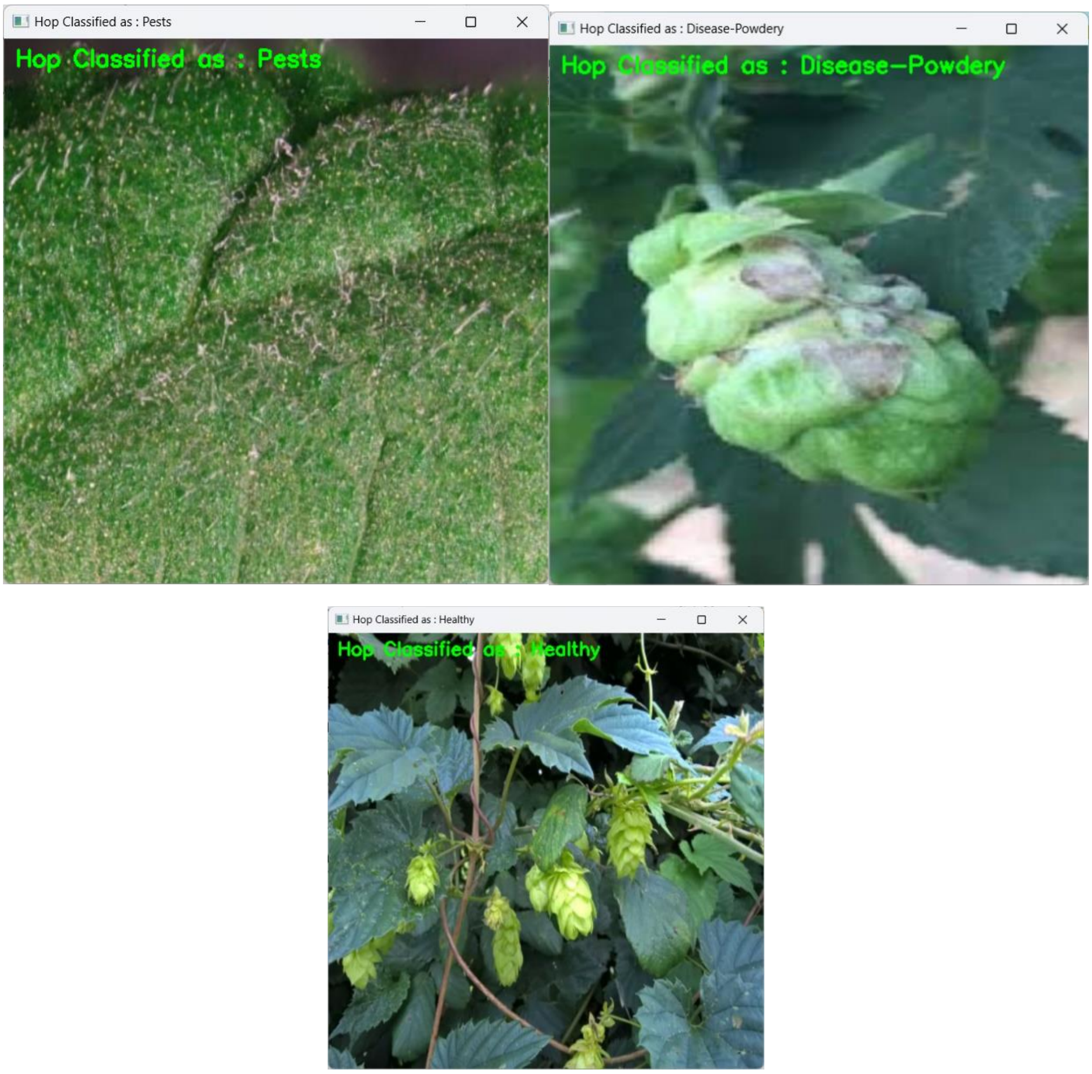

Figure 7: Prediction Results of Proposed CNN Algorithm.

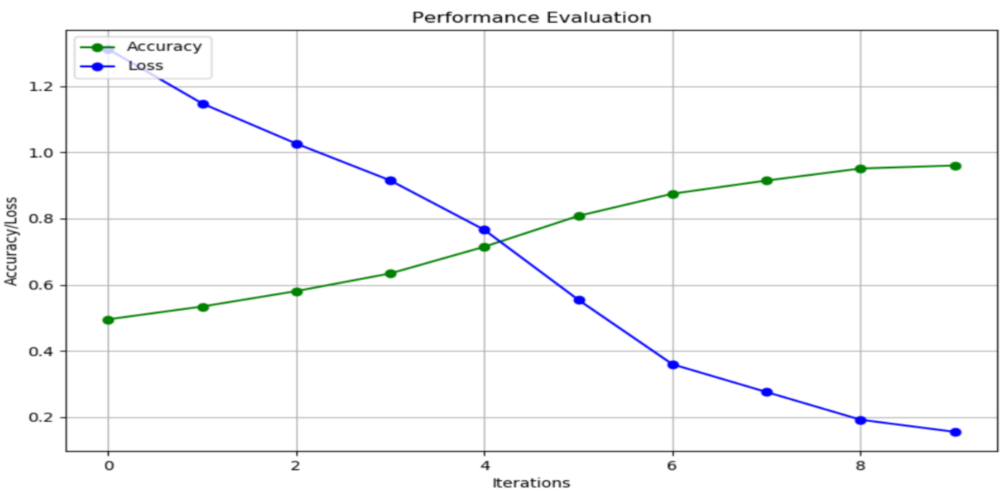

Figure 8: Accuracy and loss graph for Proposed Model

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Table 1: Performance comparison of MLP Classifier and CNN model.

Model	MLP Classifier	CNN model
Accuracy (%)	79.7	96.0

5. Conclusion

In conclusion, advanced crop classification, particularly in crops like hops, represents a significant advancement in the field of precision agriculture. By leveraging cutting-edge technologies such as machine learning and computer vision, farmers can now classify hop varieties with unprecedented accuracy. This innovation not only streamlines crop management practices but also ensures that harvested hops meet the stringent quality standards of the brewing industry. Moreover, it enhances resource efficiency, improves yields, and contributes to the sustainability of agricultural practices. Looking ahead, there are several avenues for further development and enhancement of advanced crop classification systems: As technology evolves, there is room for continuous improvement in the accuracy and efficiency of crop classification algorithms. Refining machine learning models and incorporating more sophisticated features can lead to even better results.

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