DEEP LEARNING APPROACH FOR MULTI-CLASS HOPS CLASSIFICATION FOR YIELD IMPROVMENT

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ABSTRACT

Agriculture, the bedrock of human civilization, sustains life and fuels various industries. With burgeoning global populations and shifting climate patterns, there's a growing imperative for inventive methods to optimize crop production. Precision agriculture, leveraging technology, stands as a beacon, streamlining operations, curbing resource wastage, and bolstering yields. Advanced crop classification, notably in crops like hops, presents a potential paradigm shift in this domain. Traditional agriculture leaned heavily on manual labor and basic tools. Crop categorization often relied on visual assessments by seasoned farmers, considering factors like leaf shape, colour, and fruiting attributes. While effective to an extent, this method was time-intensive, prone to human error, and ill-suited for large-scale farming. Technological strides have gradually paved the way for more sophisticated methodologies. Advanced hops classification in precision agriculture is driven by several pivotal factors. The brewing industry, a major hops consumer, demands specific varieties with distinct flavor and aromatic profiles. Accurate classification ensures the cultivation of hops that meet these requirements. Precise crop management is also crucial, optimizing resources like water, nutrients, and pest control, aligning with sustainability goals. Moreover, enhanced crop classification translates to higher yields and favorable market prices, bolstering economic viability for farmers. The challenge at hand revolves around creating a sophisticated hops classification system. This system would harness cutting-edge technology, incorporating machine learning and computer vision to differentiate between various hop varieties accurately. The goal is to enable meticulous crop management practices and guarantee that harvested hops align with the exacting quality standards of the brewing industry. Hops classification signifies a monumental leap in contemporary agriculture. By harnessing state-of-the-art technology, particularly through machine learning algorithms and computer vision, detailed images of hop plants undergo thorough analysis. These models are trained on extensive datasets, adept at recognizing subtle differences that may elude the human eye. Through this process, the system becomes proficient at classifying diverse hop varieties with remarkable precision. The outcome is a more effective and precise framework for managing hop crops, yielding higher-quality harvests for the brewing industry. This pioneering approach not only augments yields and resource efficiency for farmers but also ensures a reliable, high-quality supply chain for the brewing sector.

Keywords: Hops classification, Predictive analytics, Deep learning, KLDA features.

1. INTRODUCTION

In the realm of precision crop management and the pursuit of quality harvests, the evolution of hops classification has played a pivotal role in enhancing agricultural practices and ensuring optimal yields. The history of advanced hops classification is a narrative of continuous innovation, driven by the need for precision in cultivation and the desire to achieve superior crop quality. The origins of hops cultivation can be traced back to ancient times, with the earliest documented use dating to the Roman Empire. However, it was not until the Middle Ages that hops gained prominence in brewing, particularly in the production of beer. Over the centuries, as the demand for hops grew, so did the necessity for a more refined classification system to cater to the diverse requirements of brewers and farmers alike.

The initial classifications were rudimentary, often based on observable traits such as plant height, cone size, and color. As the scientific understanding of plant genetics advanced, so did the sophistication of hops classification. The integration of molecular biology and genetic research allowed for a more nuanced categorization, taking into account the genetic makeup of different hop varieties. In recent decades, the advent of advanced technologies, including high-throughput sequencing and genetic mapping, has revolutionized the classification of hops. This has led to the identification of specific genes responsible for desirable traits such as aroma, bitterness, and disease resistance. As a result, breeders have been able to develop new hop varieties with tailored characteristics to meet the demands of both brewers and agricultural conditions. Precision crop management, a contemporary approach to farming, has seamlessly integrated with advanced hops classification. This synergy allows farmers to optimize resources such as water, fertilizers, and pesticides based on the specific needs of each hop variety. Data-driven decision-making, enabled by sensors, drones, and other precision agriculture technologies, has further elevated the efficiency and sustainability of hop cultivation. The implications of advanced hops classification extend beyond the farm gate. Breweries now have access to a diverse array of hops, each with its own unique flavour and aromatic profile. This has sparked a renaissance in craft brewing, as brewers experiment with different hop varieties to create distinctive and high-quality beers.

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]

3. PROPOSED SYSTEM

3.1 Overview

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). 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.
- 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.

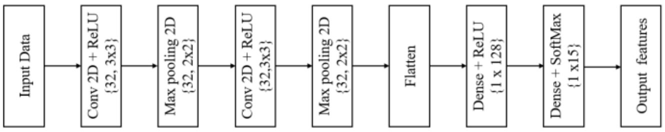


Figure 1: Proposed Architecture Diagram of Hops Classification Model.

3.2 KLDA

The principle of KLDA can be illustrated in below Fig.2. Owing to the severe non-linearity, it is difficult to directly compute the discriminating features between the two classes of patterns in the original input space (left). By defining a non-linear mapping from the input space to a high-dimensional feature space (right), we (expect to) obtain a linearly separable distribution in the feature space. Then LDA, the linear technique, can be performed in the feature space to extract the most significant discriminating features. However, the computation may be problematic or even impossible in the feature space owing to the high dimensionality. By introducing a kernel function which corresponds to the non-linear mapping, all the computation can conveniently be carried out in the input space. The problem can be finally solved as an eigen-decomposition problem like PCA, LDA and KPCA.

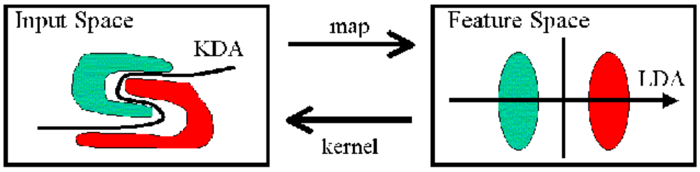


Fig. 2: Kernel discriminant analysis.

3.3 CNN

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from.

Convolution layer 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 $F(k_x, k_y, d)$..

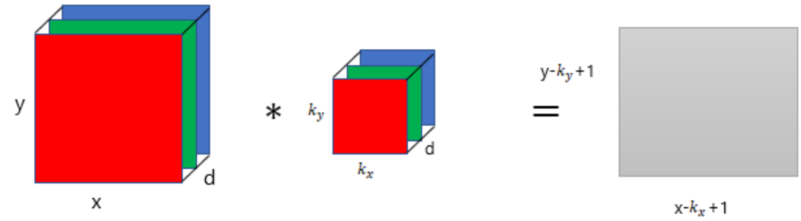
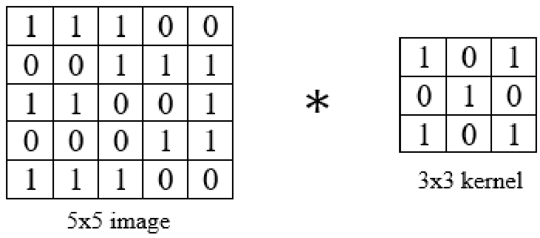
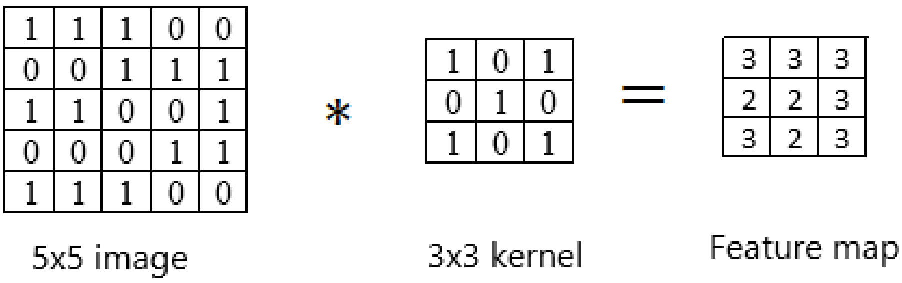


Fig. 3: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. 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.



(a)



(b)

Fig. 4: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

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.

Advantages of proposed system

- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.
- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

4.RESULTS

Figure 5 shows a screenshot or visual representation of the graphical user interface (GUI) of the application created for hops classification. It includes buttons, input fields, and other elements for user interaction. Figure 6 displays an image or images from the dataset after it has been uploaded. It provides a visual representation of the data that will be used for training and testing the classification models. Figure 7 show examples of images from different classes (Pests, Nutrient, Healthy, Disease-Powdery, Disease-Downy) after preprocessing. It could include visualizations or statistics that describe how the images have been prepared for the machine learning models.

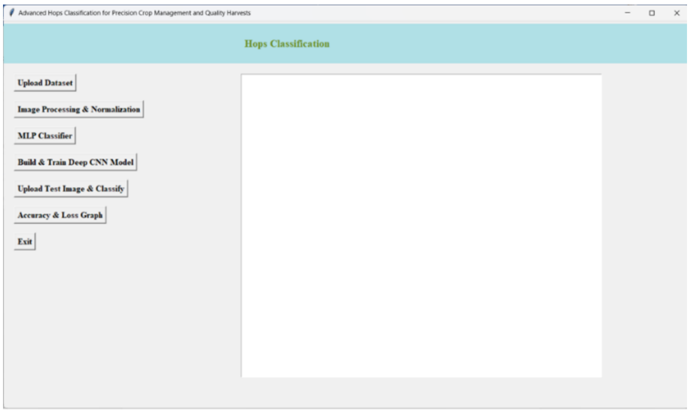


Figure 5: User interface application of proposed Deep learning Approach for Hops Classification.

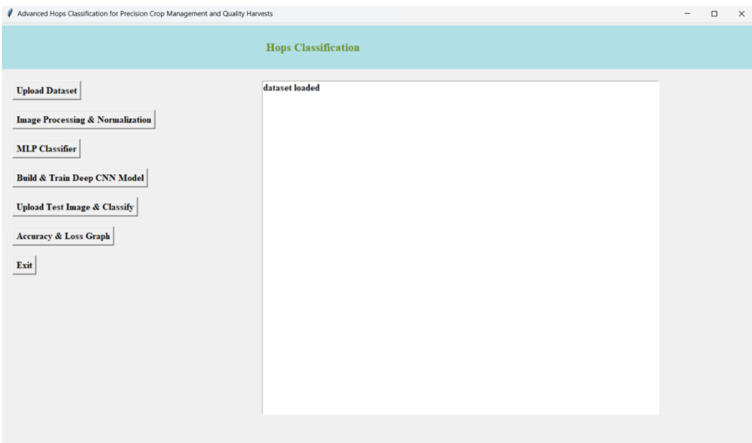


Figure 6: Illustrates the image after uploading the dataset.

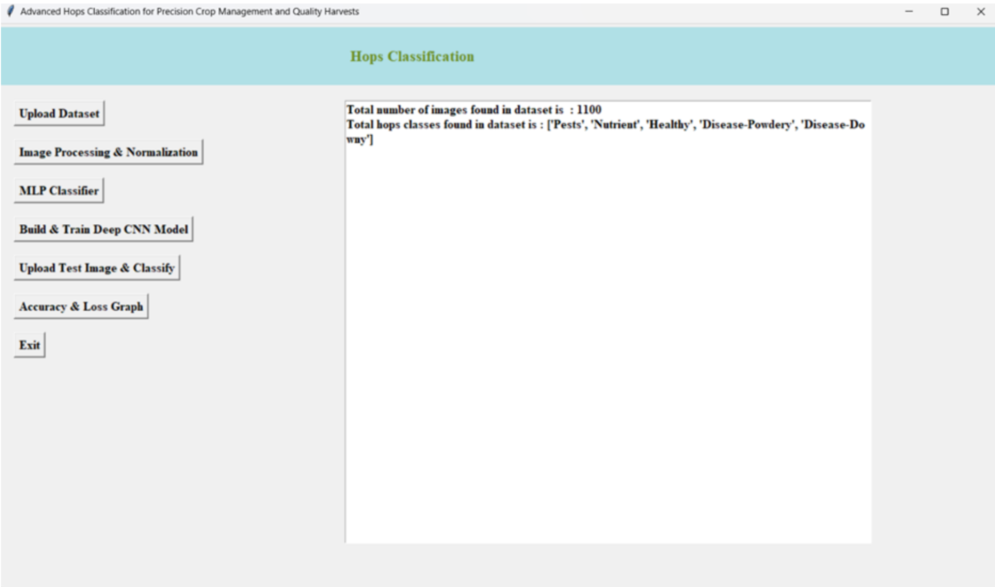


Figure 7: Illustration and Description of classes after preprocessing.

Figure 8 presents a visualization or numerical representation of the accuracy achieved by the existing Multi-Layer Perceptron (MLP) classifier. It might include metrics indicating how well the model performs on the validation or test set. Figure 9 is a graphical representation of the confusion matrix for the existing MLP classifier. The confusion matrix shows how well the classifier performs in terms of true positives, true negatives, false positives, and false negatives for each class. Figure 10 shows the accuracy achieved by the proposed Convolutional Neural Network (CNN) algorithm. It could include metrics indicating the performance of the CNN model on the validation or test set.

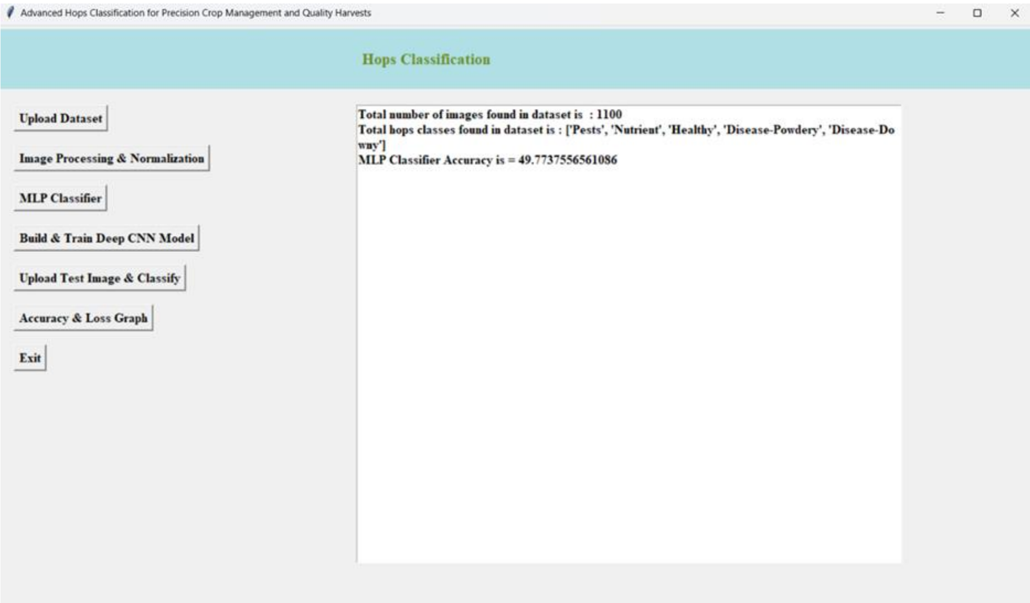


Figure 8: Model accuracy of Existing MLP Classifier.

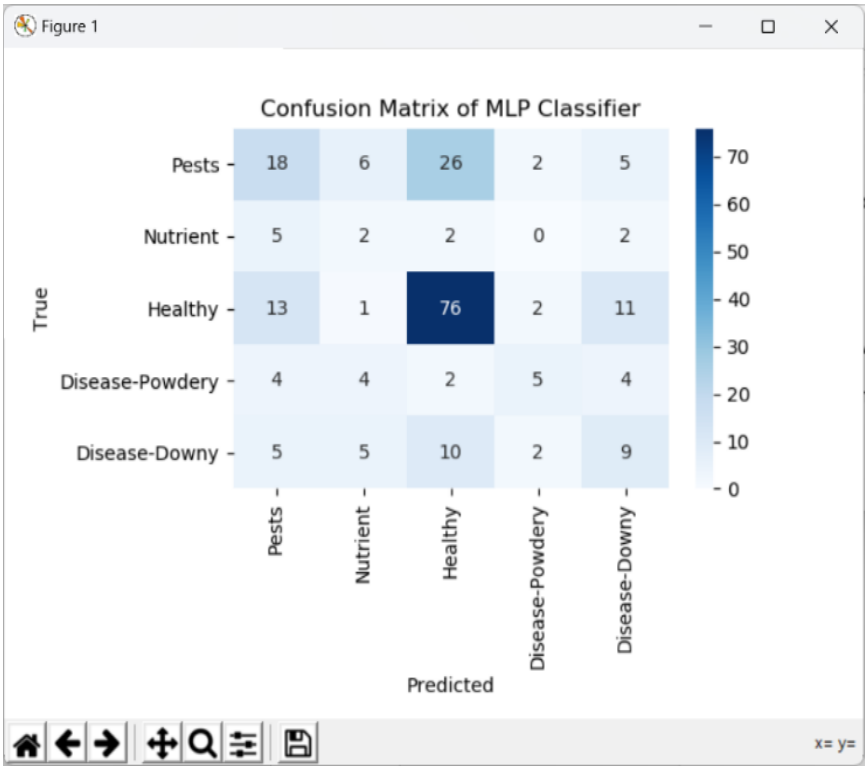


Figure 9: confusion matrix of existing MLP Classifier

Figure 11 provides a summary or visualization of the architecture of the proposed CNN model. It may include details such as the number of layers, type of layers, and the flow of information through the network. Figure 12 displays the results of the predictions made by the proposed CNN algorithm on sample images. It might show the original images alongside the predicted classes. Figure 13 depicting the accuracy and loss over training epochs for the proposed CNN model. It provides insights into how well the model is learning from the training data and how its performance changes over time.

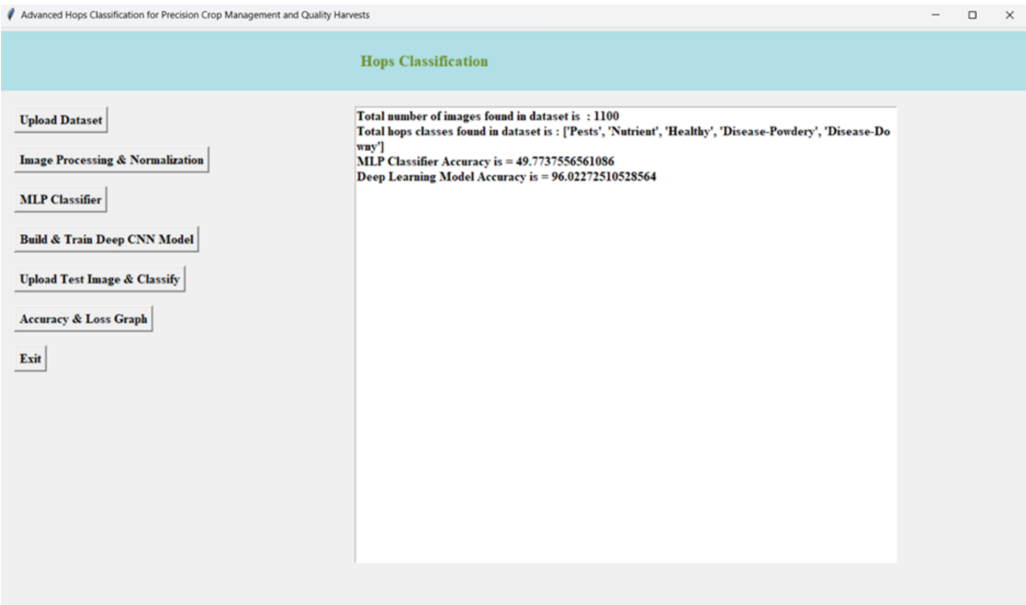


Figure 10: Model Accuracy of proposed Deep learning CNN Algorithm

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_________________________________________________________________
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 11: Model summary of proposed CNN Architecture

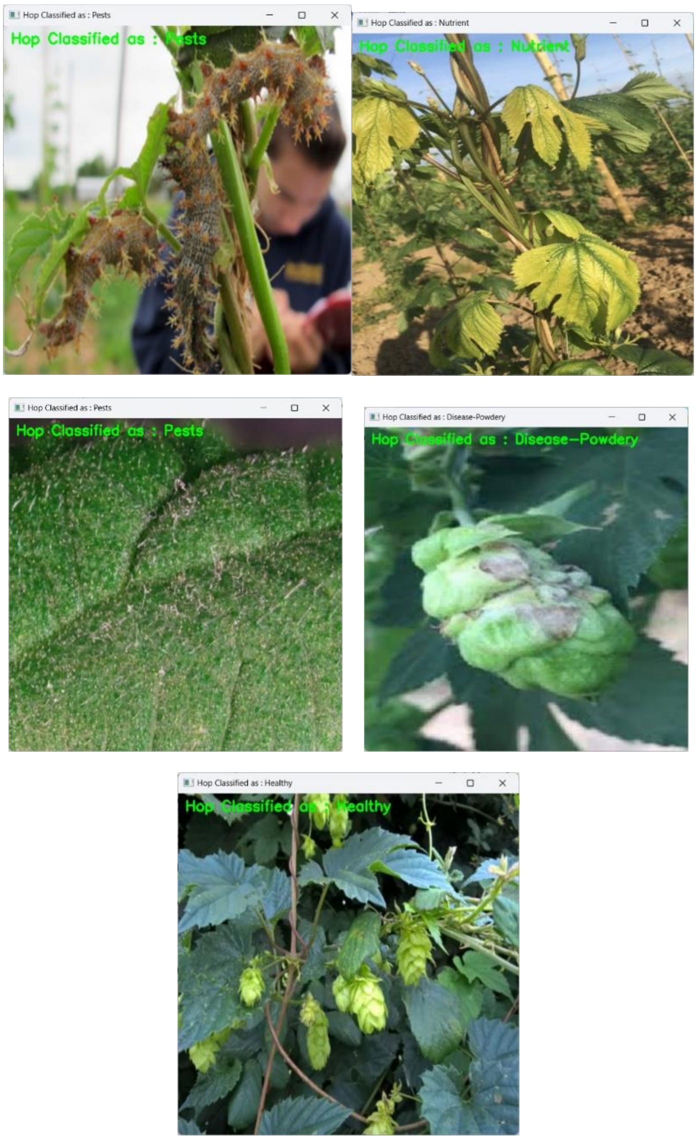

Figure 12: Prediction Results of Proposed CNN Algorithm

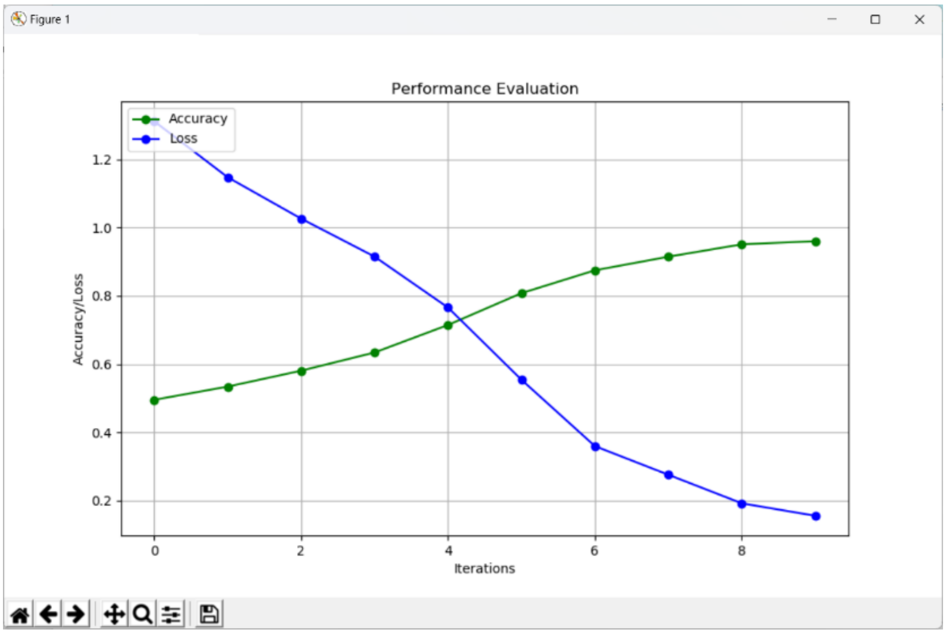

Figure 13: Accuracy and loss graph for Proposed Model

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

Model	MLP Classifier	CNN model
Accuracy (%)	79.7	96.0

For the MLP model:

— The Accuracy is 79.7, indicating the accuracy between the actual and predicted values

For the CNN model:

— The Accuracy is 96.0, indicating the accuracy between the actual and predicted values.

5. CONCLUSION

The significance of this technology lies in its potential to optimize resource allocation, enhance decision-making processes, and ultimately increase the efficiency of hops farming. With accurate classification, farmers can tailor their cultivation practices to the specific needs of each hop variety, thereby maximizing yield and minimizing resource wastage. This targeted approach to crop management is crucial for achieving sustainability in agriculture and meeting the growing demand for high-quality hops. Moreover, the implementation of the advanced hops classification system contributes to the overall improvement of crop quality. By ensuring that each hop plant receives tailored care, farmers can expect more uniform and superior yields. This not only benefits the growers but also positively impacts downstream industries, such as craft breweries, by providing a more consistent and desirable raw material for brewing. As we look toward the future, there are several exciting avenues for further exploration and development in this field. Firstly, continuous refinement and enhancement of the classification algorithms can improve the system's accuracy and versatility, accommodating new hop varieties and evolving agricultural practices. Additionally, integrating real-time data and monitoring capabilities into the system can enable farmers to respond promptly to changing environmental conditions and optimize their interventions accordingly. The future scope also extends to the integration of the Internet of Things (IoT) and other emerging technologies. Smart sensors and devices can be employed to gather additional data on factors like soil moisture, temperature, and nutrient levels, providing a more comprehensive understanding of the growing environment. This holistic approach can further fine-tune cultivation strategies and contribute to the development of a fully automated and adaptive hops farming system.

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