Convolutional Neural Network Based Crop Monitoring

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Abstract: To ensure sustainable crop production, farmers need to focus on efficient farming practices such as crop health, soil health, pest control and yield analysis. This process relies on reliable monitoring of disease and ripeness classification. This paper provides a machine learning system that classifies the crop images based on ripeness and detect diseases. Here for Feature extraction, we use Histogram of oriented gradients, for ripeness classification we use logistic regression and for disease classification we use Convolutional Neural Networks. To implement this system, we are using flask-based web interface where it ensures seamless deployment and we have visual tools like bar chart, pie chart to improve readability. More-over this system provides insights to nutrient management to optimize yields and reduce crop losses. A voice enabled feature enables that farmers can retrieve the information about yield analysis, nutrient management, remedial measures, and disease classification. This system improves efficient crop monitoring where it can minimize the errors from manual inspection, to maintain sustainable agricultural productivity and it supports decision making based on data to enhance crop health and yield impact.

1 INTRODUCTION

Agricultural productivity is the core element of food security and economic stability. To maintain the proper balance between yield and sustainability, we need to be aware of crop diseases and quality monitoring inefficiencies. Ensuring timely identification of the diseases and proper assessment of ripeness is important to meet the demands of global food production. To implement this process, we have technological innovations, especially in machine learning and deep learning models offer solutions to these problems, which enable farmers to make informed decisions and maintain good crop production.

This proposed work involves machine learning models to classify crop diseases and ripeness, addressing crucial aspects regarding agricultural monitoring. Features are extracted using Histogram of Oriented Gradients (HOG); we classify crop ripeness using logistic regression, and we classify crop diseases using convolutional neural networks. The provided system performs very well against all metrics, where it achieves a high accuracy demonstrated by an F1 score of 92.3%. It ensures reliability and effectiveness in real-world applications.

A seamlessly integrated web-based solution developed by using Stream-lit and Flask. It ensures that accessibility and ease of use are available to users. The system provides various visualizations to enhance decision-making, including disease yield impact analysis, disease distribution pie charts, disease progression timelines, and nutrient requirement analysis. These insights help farmers and researchers to improve decision-making ability so that in the future they will get better results, and also they will evaluate classification accuracy, disease trends, and crop health in real time.

Additionally, disease classification, the solution offers a recommendation system where it includes nutrient management recommendations to optimize yield and minimize crop issues. It offers a voice-enabled feature that helps farmers to analyze disease

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effects and predicted yields by delivering analyses and suggesting corrective actions. This solution automates the process of monitoring crops, which reduces manual errors, enhances classification accuracy, and tackles agricultural issues related to diseases. This leads to greater productivity and improved crop quality and plays a part in global food security.

2 RELATED WORKS

In precision agriculture, classifying plant diseases with the help of convolutional neural networks is essential. Sharma, R., & Jain, A. (2020) To identify crop diseases from visual attributes such as color, shape, and texture, we employ image processing methods like convolutional neural networks. In the past, many existing machine learning models, like support vector machine (SVM), k-nearest neighbor (K-NN), and random forests, relied on manual inspection for feature extraction, with time being a critical factor as well. Shah, M. et al, (2019). Convolutional neural network (CNN) is considered as the best technique in this field, and it automatically extracts spatial features and improves highly accurate disease classification. Earlier, Mohanty et al (2016) achieved over 99% accuracy in identifying 38 crop diseases using CNNs. Barbedo, J. G. A. (2019) We have open datasets like Plant Village; it includes all types of diseases where we identify common tomato diseases.

Simonyan, K., & Zisserman, A. (2014). To improve harvesting techniques and maintain quality control, ripeness classification is essential. Existing manual methods lead to errors, are time-consuming, have limited accuracy, and depend on human judgment, while new technology innovations like machine learning models and computer vision techniques are used to classify ripeness based on features like shape, color, and texture. Qin, Z. (2016).To identify ripeness, colour is a key indicator, with colour space transformations (eg. RGB to HSV) and histogram analysis to access ripeness stages. Hinton, G.E., et al, (2012). New advancements involve CNNs to train on labelled datasets to achieving high accuracy in classifying ripe, unripe, old and damaged crops. Ivanovici, M. et al, (2024) Lighting variations are addressed through techniques and solved using data processing techniques.

Recommendation systems provide actionable insights to farmers to mitigate diseases and to analyze yield impact. These systems suggest soil nutrients, yield impact, nutrient requirements, remedial measures, and a voice-enabled feature where it can help farmers to interact and know more about the harvesting problems. Earlier, research by Singh et al. (2018) implements a hybrid recommendation system that combines rule-based systems and filtering to recommend best practices to farmers regarding plant diseases. Moreover, nutrient management has been highlighted as a key indicator in improving harvesting and recovery.

Bochtis, D. et al, (2018). Image-based classification and recommendation systems have faced so many challenges, such as environmental factors (lighting, background clutter), image quality like low-resolution images, blurry images, and not being suitable for large datasets [10]. In the future, the advanced technologies used for agricultural disease management involve integrating IoT sensors, cloud computing, and AI platforms for data collection and analytics. This method improves model performance and gets better results for disease classification and recommendations while improving scalability. Moreover, the incorporation of multilingual voice outputs enhances the accessibility of this work for farmers aiming at sustainable crop production.

3 DESIGNED SYSTEM

The designed system is used to show the detailed description on how the images are analyzed and it also focuses on two main objectives: ripeness detection and disease classification. Figure 1 illustrates how the system works on the images dataset and the images are divided into two types: Ripe Images and Disease images, we need to select which types of images we are choosing and when the ripeness classification option is chosen the system performs ripeness classification over the image and determines how ripen is the fruit or vegetable and if the disease detection option is selected the system performs disease classification and identifies what kind of disease it is and displays the severity of the disease over a graph scale.

After the disease classification and ripeness classification, the next step is visualizations where the learned data is represented in an interpretable format so that farmers can easily understand it by observing it. Users can then have three options to make action selections, such as prediction, recommendation, or both. Prediction can give brief description about the disease name and yield analysis, while recommendation provides actionable information, including nutrient requirements and management suggestions and while selecting both, it provides both prediction and recommendation analysis in a comprehensive way offering in depth evaluation. The final step involves a voice response feature, delivering the results in a user-friendly manner and an understandable way, providing actionable insights to the user.

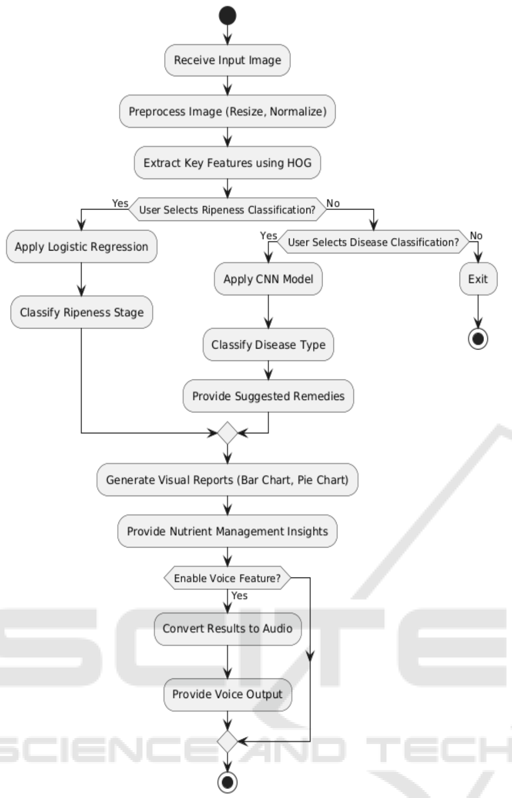

Figure 1: Proposed system for crop monitoring.

Figure 1 - The proposed system involves technologies such as machine learning and image processing to improve agricultural productivity and decision-making. It effectively leverages advanced methods to get actionable insights, supporting farmers to have efficient crop yield and sustainable farming. This will reduce manual errors and increase crop production, which results in better productivity, and this will benefit farmers to get better yield production.

4 IMPLEMENTATION

4.1 Preprocessing Techniques

Picture Scaling and Normalization: Picture scaling is used to resize the image depending on their size as the data can be in different sizes typically, they are of 224x224 pixels, to ensure the linearity in the dataset, normalization is used in resizing the images pixel values to the range of (0,1) this improves model’s intersection.

Data Augmentation: Data Augmentation is used to improve the diversity of training data and also reduces overfitting, it also involves some techniques such as rotation, flipping, zooming and adjustments on brightness are applied. This step not only increases the size of dataset but also allows the model to normalize in a much simpler way by learning from different examples.

Label Encoding: Each and every image in the dataset is labelled and also helps to indicate or identify the type of class such as healthy, blight or ripe. These labels are again converted into numerical values in order to serve as inputs during the model’s training.

Noise Removal and Image Filtering: Lack of better resolution in image and irrelevance in the content or excessive noise are eliminated in order to maintain the dataset’s integrity. This step promises that the model is properly trained with data which is more precise and accurate.

4.2 Methodologies

An experimental design is chosen in this research. The reason behind this is to improve and validate a hybrid system that detects multiple diseases in a tomato plant and also performs ripeness classification. The ultimate goal was to integrate feature extraction using Histogram of Oriented Gradients (HOG) and to perform image classification using Convolutional Neural Networks (CNN) in order to achieve the prediction that are more precise and trustworthy. This research methodology also involves preparation and preprocessing of datasets, feature extraction, model training, deployment and evaluation. A web application that was interactive towards the users was developed to make the system more user friendly.

4.2.1 Feature Extraction Using HOG

The Histogram of Oriented Gradients (HOG) is used to extract features that are more robust in nature while performing the tasks. Figure 2 illustrates the working of feature extraction using HOG.

The primary step for feature extraction begins with an original image that contains raw data, after that aligning the image according to the standards. The image resized has a fixed dimension of 128x128 pixels this process can be applied to multiple images by applying the consistent feature. Later the input image is divided into non-overlaying cells with a pixel size of 16x16, this step is important as it captures all the local features, structure and texture of the image. The fifth step Gradient computation is an important step in HOG it measures the pixel intensity of an image its main purpose is to detect sharp edges, shapes, texture of an image. After the Gradient computation step the fifth step is Feature Vector Generation which is used to divide the image into small cell of 8x8 size where each cell has HOG in different direction, the final result is a feature vector representing edges, contours, patterns, and texture of an image.

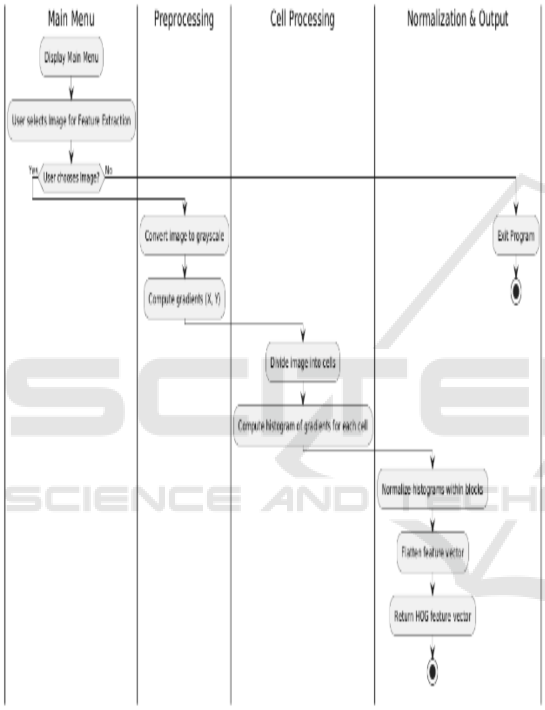

Figure 2: Feature extraction.

4.2.2 CNN Architecture

CNN plays an important role to process and classify the image based on the disease. Figure 3 explains the architecture of convolutional neural network, the input for the model leaf image dimensions is 128x128x3 and passes through several layers, Input layer is the first layer where images are represented in RGB and all the images are resized into 128x128x3 pixels for uniformity, after this convolution layer 1 model is used, this uses 32 filters with a dimension of 3x3 along with RELU function. It takes of extra features like edges, shapes, patterns, etc.., the next step is Max Pooling Layer 1 where the pooling size is 2x2 filter is used to reduce the dimensions for a feature map to 64x64x32 while retaining essential features this layer also reduces the noisy input data.

Now the Convolution Layer 2 is used where the filters are increased from 32 to 64 to detect more complexes, kernel size of 3x3 is used along with the RELU function, this layer is used to extract specific disease patterns. The fifth step is Max Pooling Layer 2 this layer performs with pooling size of 2x2 to reduce further dimensions for feature map 32x32x64 and retains all essential features, now the Convolution Layer 3 is used where the filters are increased from 64 to 128 to identify more complex patterns, it also uses 3x3 kernel along with RELU function this layer is used to detect irregular textures and patterns in the image. Flatten layer is the next step where multi-dimensional maps convert into 1D array, this process is done for the next layer's input process which is dense layer. Dense layer performs to learn high level relationships between extracted features. It requires 512 neurons along with the RELU activation function. Dropout regularization is also performed to prevent overfitting. The final step Output Layer consisting of 10 neurons, corresponding to disease classes where a SoftMax activation function is used to assign probabilities for each disease class and it enables multi-class classification.

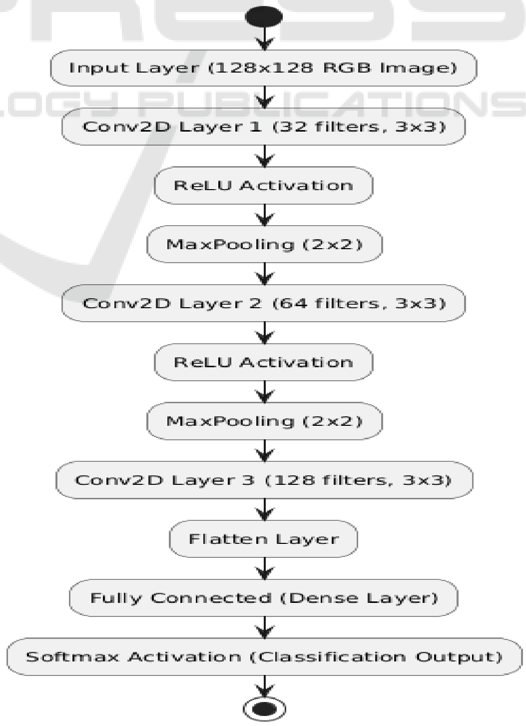

Figure 3: Convolutional neural network.

5 RESULTS AND ANALYSIS

This section is very crucial for any model. Results and Analysis section is to analyze model performance. It involves analyzing the experiments outcomes and comparing the proposed solution with existing model. So that we can get an idea about the proposed model performance.

5.1 Evaluation Metrics

Accuracy: Accuracy is a crucial evaluation metric to assess model performance. This model achieves an accuracy score of 93% indicates the correctness in classifying plant diseases and ripeness.

Precision: Precision is an essential evaluation metric to assess model performance. This model achieves 92% indicates that a plant has a disease or a certain ripeness level. It means this model avoids making incorrect positive predictions.

Recall: Recall is an evaluation metric to assess model performance. This model achieves a recall score of 90% which indicates the model is good at identifying the correctly disease plant.

F1-Score: F1-score is an evaluation metric to assess model performance. This model achieves a F1-score of 92.3% which indicates that this model is well balanced between precision and accuracy. It also ensures that the model is both accurate and consistent. Specificity: For this evaluation metric, it achieves 94% score which explains the model's performance in identifying healthy plants.

5.2 Graphical Representation

5.2.1 Training and Validation Accuracy Analysis

Figure 4 shows the Training accuracy and Validation accuracy changes of the model performance over four epochs during the training process. In this figure, X-axis represents the number of epochs and Y-axis represents the accuracy values. As this figure describes how the model is classifying plant diseases over training and validation processes.

Blue line describes the training accuracy which increases gradually with each epoch highlighting the model's performance to adapt and improve on the training data. Orange line represents the validation accuracy which steadily increases, highlights how the model performs against unseen data.

As this progress indicates that there is a parallel improvement in both training and validation accuracy which explains the model balanced learning process. Gap between two accuracies is relatively small which shows there is no chance for overfitting and underfitting. This reflects that the model adapts well to the validation dataset.

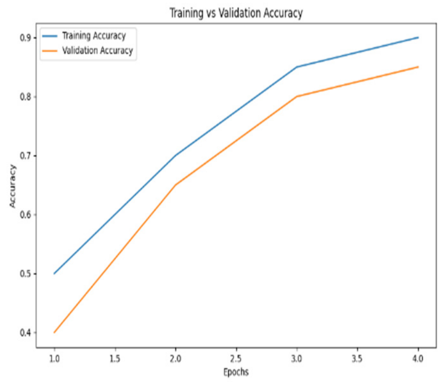

Figure 4: Training accuracy vs validation accuracy.

5.2.2 Training and Validation Loss Analysis

Figure 5 shows the Training loss and Validation loss changes of the model performance over four epochs during the training process. In this figure, the X-axis represents the number of epochs and the Y-axis represents the loss of values. As this figure assesses if your model is actually learning patterns or just identifying patterns and also prevents from overfitting.

Blue line explains the training loss which decreases gradually with each epoch illustrating the model is learning from the training data. Orange line represents the validation loss which decreases rapidly over epochs represents improved performance on unseen validation data.

As both training loss and validation loss decrease over epochs suggests that the model is learning effectively and prevents overfitting.

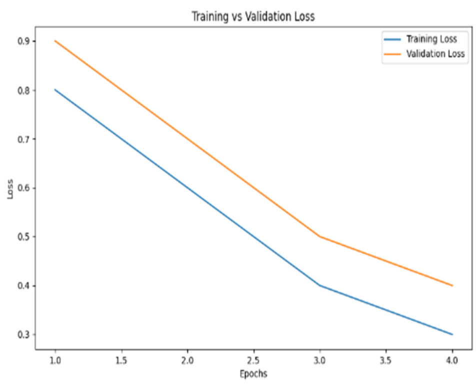

Figure 5: Training loss vs validation loss.

5.2.3 Disease Impact Severity Analysis

Figure 6 indicating heatmap showing the impact severity of various diseases on tomato yield. The X-axis represents the yield impact severity as percentage and Y-axis represents lists of diseases.

Color scale is used to represents how the disease is impacted. The color ranges from red (low impact) to green (high impact), along with intermediate shades indicating severity levels. The healthy tomato is marked with the highest yield impact (100%), the diseases show the least yield impact as 40% and 45% respectively.

This visualization helps in identifying which diseases has most significant yield impact, providing a brief overview of their impact severity.

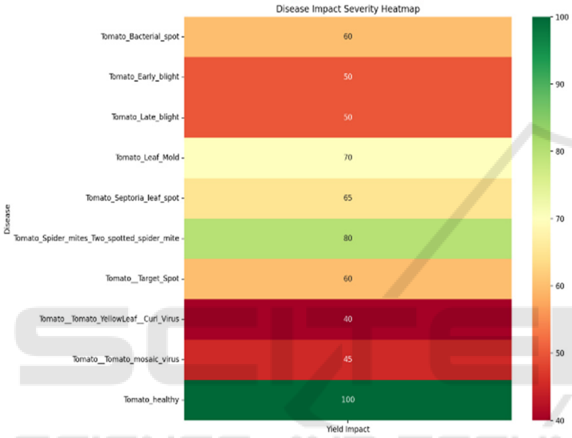

Figure 6: Disease impact severity heatmap.

6 CONCLUSION AND PROSPECTS

This research provides an in-depth explanation for disease classification and ripeness classification. Additionally, it includes visualizations to understand in detail and recommendations to improve crop yield and to reduce manual error. A voice-enabled feature is featured to provide detailed explanations about disease classification, ripeness classification, and recommendations to farmers.

For disease classification, we use a convolutional neural network to analyze images, and to extract features for ripeness classification, we use a histogram of oriented gradients.

This system provides an interface that integrates visual insights through graphical representation. These visualizations help in identifying diseases and crop yield and maximizing nutrients to improve yield. This results in reducing manual errors, improving decision making, promoting sustainable farming practices and enhancing productivity and crop health.

The proposed system has solved so many issues that were addressed previously, but apart from the existing solution, there are several areas where the proposed work needs to be expanded so that it maximizes productivity and promotes sustainable farming.

The key areas for expansion include Extension to other crops, Real-Time Monitoring and IoT Integration, Enhanced Dataset Diversity, Multi-Language Voice Assistance and Integration with Drone-Based Crop Monitoring.

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