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Detection and Classification of Saffron Plant Diseases using Machine Learning: A Research

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Abstract: Saffron, known as "red gold," is a valuable spice derived from the flower of Crocus sativus. However, saffron cultivation faces challenges due to diseases that can harm crop yield and quality. This thesis proposes a deep learning-based approach using the VGG 16 architecture to detect and classify saffron diseases. The study collects a comprehensive saffron disease dataset, organizes it by disease type, and enhances its quality through analysis and augmentation. The VGG 16 architecture, known for image classification, is adapted for saffron disease detection, utilizing convolutional and fully connected layers for feature extraction and classification. The model is trained using multiple epochs, achieving an impressive 87% accuracy. Comparison with other methods demonstrates the superiority of the proposed approach. The study utilizes high-performance computing systems for efficient evaluation. Overall, this research demonstrates the potential of deep learning in saffron disease management, aiding farmers in effective decision-making for disease control measures.

Keywords: Saffron, Diseases in Saffron, Machine learning, VGG

I. INTRODUCTION

Saffron, scientifically named Crocus sativus, is a highly valued spice recognized for its unique scent, strong flavor, and vibrant golden hue. It is obtained from the crimson stigmas of the saffron flower, which are meticulously harvested and dried. Saffron threads are delicate and composed of three parts: the red stigma, yellow-style, and white filament. Cultivating saffron is a labour-intensive process due to the meticulous care required. The saffron crocus plant belongs to the Iridaceae family and has slender, violet flowers. Each flower produces only three stigmas, and a large number of flowers are needed to yield a small amount of saffron. It takes approximately 150,000 flowers to produce one kilogram of saffron. The objective of this study is to develop an automated and accurate method using the VGG 16 architecture to detect and classify diseases that affect saffron plants. By leveraging deep learning techniques, the study aims to overcome the challenges associated with manual disease detection in saffron farming.

A. Diseases in Saffron

Saffron, like other crops, is prone to several diseases that can have adverse effects on its growth, yield, and quality. Below are some prevalent diseases that can impact saffron plants.

1) Corm Rot (Rhizoctonia crocorum):

Corm rot is a fungal disease caused by Rhizoctonia crocorum, affecting saffron corms. It begins with small, wet spots on the corm surface that grow larger and become brown. Infected corms become soft, decayed, and negatively impact plant growth and flower production. Excessive moisture, inadequate drainage, and improper corm storage conditions can contribute to the spread of this disease [4].

Figure 1Corm rot in Saffron

2) Fusarium Wilt (Fusarium oxysporum):

Fusarium wilt is a fungal disease caused by Fusarium oxysporum that affects saffron plants. It disrupts the plant's vascular system, leading to leaf yellowing, wilting, and necrotic streaks. Crop rotation and soil management are important for disease control due to the pathogen's long persistence in the soil [5-6].

3) Leaf Blight (Cercospora spp.):

Leaf spot or leaf blight is a fungal infection caused by various types of the Cercospora fungus. It appears as round or irregular brown spots on saffron leaves, usually with a yellow ring around them. The spots can merge together, forming larger dead areas. Severe cases can cause the leaves to fall off, impacting the plant's ability to perform photosynthesis. Leaf spot is more likely to occur when saffron leaves remain wet for long periods, humidity levels are high, and saffron plants are crowded together [7].

Figure 2 Leaf Blight in Saffron

4) Corm Rot (Sclerotinia spp.):

Sclerotinia corm rot is caused by fungi belonging to the Sclerotinia genus. The disease primarily affects saffron corms, causing their decay. Infected corms become soft, spongy, and rot, with white fluffy mycelium and black, hard resting structures called sclerotia present. Sclerotinia corm rot can lead to reduced plant vigor, decreased flower production, and even plant death. Factors such as cool and moist conditions, excessive irrigation, and poor soil drainage contribute to the development and spread of the disease. [8, 9]

II. LITERATURE REVIEW

“Detection and classification of saffron corm diseases using a machine learning approach “by Alavijeh et al. (2009) [11] focused on the use of hyperspectral imaging for saffron disease detection. They highlighted the non-destructive nature and rapidity of this technique, which captures images across a wide range of spectral bands. Their work emphasized the analysis of hyperspectral data using machine learning algorithms to classify healthy and diseased saffron plants based on spectral signatures.

“Classification of saffron plant diseases using image processing and machine learning techniques” by Prakash et al. (2010) [12]. explored the application of computer vision and deep learning techniques for saffron disease detection. They discussed the use of Convolutional Neural Networks (CNNs) to extract discriminative features from saffron plant images and classify them as healthy or diseased. Their work emphasized the advantages of scalability, efficiency, and potential for real-time disease detection offered by automated methods based on deep learning.

III. OBJECTIVES

1) Developing a saffron disease detection model using the VGG 16 architecture to accurately identify and classify saffron plant diseases based on visual symptoms.
2) Training the VGG 16 model with a diverse dataset of saffron plant images to improve its ability to recognize and differentiate between different saffron diseases with high accuracy.
3) Evaluating the model's performance by measuring precision, accuracy, and loss to assess its effectiveness in accurately detecting and classifying saffron diseases.
4) Investigating the model's transferability and generalizability across different saffron cultivation regions and environmental conditions to ensure its applicability in various farming contexts.
5) Exploring methods to interpret and visualize the learned features of the model, enhancing transparency and providing valuable insights for saffron farmers and stakeholders in the disease detection process.

IV. METHODOLOGY

A. Methodology in saffron disease detection and Identification

Methodology involves several steps that are as under

1) Dataset Collection from Saffron Research Centre

Obtain a diverse collection of saffron plant images from trusted sources, such as the saffron research center, ensuring that the dataset includes images of both diseased and healthy plants. The dataset should be properly labeled, with accurate annotations for each disease. It is important to have an adequate number of samples for each disease class to ensure balanced training.

2) Segregation of Data into Respective Folders and Different Diseases

Organize the dataset by creating separate folders for different saffron diseases and healthy saffron plants. Utilize file management libraries like 'os' in Python to automate the process of moving the saffron plant images into their corresponding disease folders or the folder for healthy plants. This ensures accurate labelling and categorization of the data.

3) Import Libraries

Install the required libraries using package managers like pip or conda. For example, use pip install tensorflow and pip install keras to install TensorFlow and Keras, respectively.

Import the necessary libraries in your Python script using import statements. For example, import tensorflow as tf and from keras import layers will import the TensorFlow and Keras libraries, respectively.

4) Dataset Analysis and Augmentation

Conduct exploratory data analysis (EDA) on the dataset, employing tools like NumPy and Pandas to compute statistics, visualize class distributions, and detect data imbalances. Employ Keras' ImageDataGenerator library to apply data augmentation techniques, generating augmented versions of the images through random rotations, horizontal/vertical flips, zooming, and other transformations.

5) Model Design

The VGG model architecture is implemented using the Keras framework. It involves sequentially stacking convolutional layers and pooling layers, with the option to include fully connected layers for classification. The Conv2D layer in Keras is used to define the convolutional layers, specifying the number of filters, kernel size, activation function, and padding. Max pooling is applied using the MaxPooling2D layer to reduce the spatial dimensions. Regularization techniques like dropout or batch normalization can be added to enhance model performance and prevent overfitting..

6) Model Compilation

In Keras, create the VGG model using the compile () function. Set the optimizer, including parameters like learning rate and decay rate. Select an appropriate loss function for multi-class classification. Define the evaluation metric(s) such as accuracy using the metrics parameter.Training the Data

The dataset is divided into training and validation sets using functions like train_test_split() from scikit-learn. The VGG model is trained on the training data using the fit () function in Keras, specifying the necessary parameters such as number of epochs and batch size. Callbacks, such as early stopping or model checkpoints, are employed to monitor the training process and prevent overfitting.

7) Plotting Graphs

During training, record the training and validation metrics using the history object returned by the fit () function.

Use data visualization libraries like Matplotlib or Seaborn to plot line graphs or bar plots showing the trends of metrics, such as accuracy.

Figure 3Model Workflow

V. SYSTEM IMPLEMENTATION

The VGG-16, developed by the Visual Geometry Group at the University of Oxford, is a popular convolutional neural network (CNN) architecture widely utilized in computer vision. It is particularly well-known for its effectiveness in image classification tasks, such as identifying and categorizing saffron diseases. This paper provides an overview of the VGG-16 architecture and its practical implementation.

A. Architecture

The VGG-16 architecture is highly regarded for its simplicity and efficiency. It comprises multiple convolutional layers stacked together, followed by fully connected layers used for classification. Here are the essential characteristics of the VGG-16 architecture.:

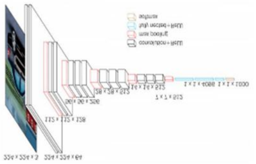


Figure 4 VGG 16 Detailed Architecture with layers

1) Convolutional Layers

The network consists of 13 convolutional layers that use 3x3 filters to capture detailed image features. These layers are arranged in a sequential manner, with each layer containing a specific number of filters. The depth of the network allows it to learn intricate and hierarchical features, enabling more sophisticated image analysis..

2) Pooling Layers

Max pooling layers with a 2x2 filter and stride of 2 are used to down sample the feature maps after each set of convolutional layers. This helps reduce computational complexity while preserving essential information.

3) Fully Connected Layers

In the later stages of the network, following the convolutional and pooling layers, there exist three fully connected layers that serve as a classifier. These fully connected layers play a role in gathering overall information and generating the final predictions. The VGG-16 architecture is employed for the detection and classification of saffron diseases.:

4) Model Initialization

Develop a sequential model using a deep learning framework such as Keras or PyTorch. Include the required convolutional layers with suitable settings like the number of filters, kernel size, and activation function. Incorporate max pooling layers between the convolutional layers to reduce the size of the feature maps.

5) *Fully Connected Layers*

The output of the final convolutional layer is flattened and connected to fully connected layers. The number of neurons in the fully connected layers is adjusted according to the complexity of the classification task. An activation function like ReLU or sigmoid is applied to introduce non-linearity.

6) *Model Compilation*

Choose the optimizer (e.g., Adam or SGD) and set the learning rate and hyperparameters accordingly. Pick a suitable loss function, such as categorical cross-entropy, for multi-class classification. Specify evaluation metrics, like accuracy, to track the model's performance during training.

7) *Training the Model*

Split the pre-processed saffron dataset into training and validation sets. Feed the training data into the VGG-16 model and iteratively update the model's weights using backpropagation and gradient descent.
Adjust the number of epochs and batch size based on the dataset size and computational resources.

8) *Model Evaluation and Prediction*

Utilize the VGG-16 model to predict the disease type of new saffron plant images. By employing the VGG-16 architecture and fine-tuning it on saffron plant images, we can accurately detect and classify saffron diseases, facilitating effective disease management and cultivation practices.

9) *Parameters for Assessing model performance.*

When assessing the performance of the saffron disease detection and classification model, several evaluation metrics are commonly used. These metrics provide insights into the model's accuracy, validation accuracy, validation loss, and loss. Here's a brief explanation of each metric:

10) *Accuracy*

Accuracy is a metric that evaluates the correctness of a model's predictions. It is determined by dividing the number of correctly classified samples by the total number of samples. A higher accuracy score indicates a more effective classification performance.

11) *Validation Accuracy*

Validation accuracy measures the model's accuracy on a separate dataset called the validation dataset. This dataset is used during training to evaluate the model's performance on unseen data. It provides an indication of how well the model can handle new samples and identify saffron diseases.

12) *Validation Loss*

Validation loss is a metric that evaluates the disparity between the predicted probabilities of different classes and the actual class labels in the validation dataset. It provides an indication of the model's performance and its ability to generalize to new data. A lower validation loss indicates that the model is successfully capturing patterns in the data and performing well on unseen examples.

13) *Loss*

Loss, referred to as training loss or training error, measures the difference between the predicted probabilities of classes and the actual class labels in the training dataset. It quantifies the disparity between the model's predictions and the true labels during the training process. The objective of training is to minimize the loss, indicating an enhancement in the model's capability to classify saffron diseases.

14) *Confusion Matrix*

A confusion matrix is a tabular representation that displays the classification results compared to the actual labels. It shows the counts of true positive, true negative, false positive, and false negative for each saffron disease class. The confusion matrix provides detailed information about the model's classification performance for individual diseases and can be used to calculate other evaluation metrics. These metrics provide a quantitative assessment of the model's accuracy and error.

Monitoring metrics such as accuracy, validation accuracy, validation loss, and loss during training helps researchers understand the model's learning progress, overfitting, and performance on training and validation datasets. Visualizing these metrics over epochs or iterations can graphically represent the model's progress and aid in decision-making for optimization and generalization. Presenting these metrics in a concise manner, such as through tables or graphs, helps stakeholders understand the model's performance. Visualizations like bar charts, pie charts, or heatmaps can highlight the distribution of metrics across saffron disease classes, revealing areas of success and potential improvement. Accurate interpretation and presentation of evaluation metrics provide valuable insights for stakeholders, researchers, and end-users, leading to informed decision-making and advancements in saffron disease detection and classification techniques.

VI. RESULTS AND DISCUSSION

The saffron disease detection model was developed using a deep learning approach and trained over multiple epochs. The accuracy improved gradually, reaching 87% after 20 epochs. The model demonstrated promising results, although further optimization and parameter tuning could enhance its performance.

A. Epoch=1

Total params: 14,815,044
Trainable params: 100,356
Non-trainable params: 14,714,688

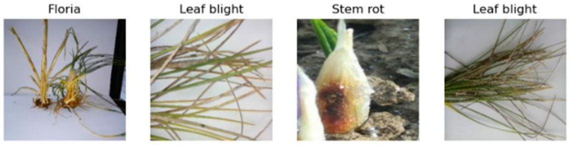


Figure 5 Types of Disease detected during Epoch 1

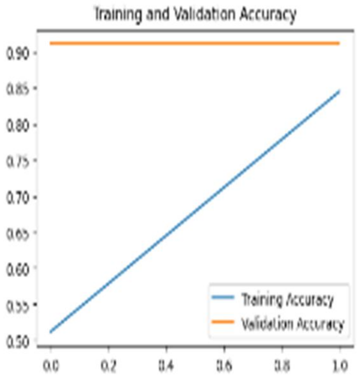


Figure 6Training and Validation Accuracy

Figure 7 Training and Validation loss at Epoch 1

Accuracy on the Test Set = 91.18 %
Model Saved!

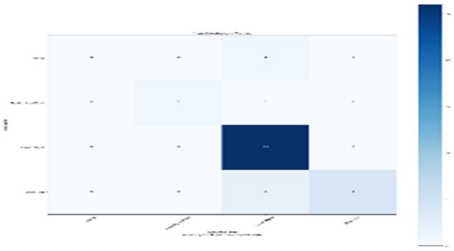


Figure 8 Confusion Matrix at epoch =1

Therefore, at Epoch 1 The recorded parameters are as under:

Table 1 Parameters and their values at epoch =1

Parameter	value
Loss	14.81
Accuracy	0.8452
Validation Loss	2.4797
Validation Accuracy	0.9118

B. Epoch =10

When the epochs are increased to 10
Total params: 14,815,044
Trainable params: 100,356
Non-trainable params: 14,714,688

Figure 9 Types of diseases recorded when the epoch =10

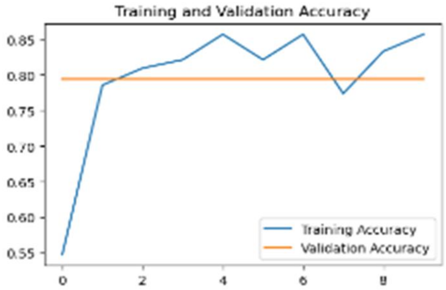


Figure 10 Validation Accuracy when Epoch =10

Figure 11 Training and testing validation loss when Epoch =10

12s 576ms/step - loss: 150.7228 - accuracy: 0.7941
Accuracy on the Test Set = 79.41 %
Model Saved!

Table 2 Parameters and values for Epoch =10

Parameter	value
Loss	150.722
Accuracy	79.41
Validation Loss	2.4797
Validation Accuracy	0.85

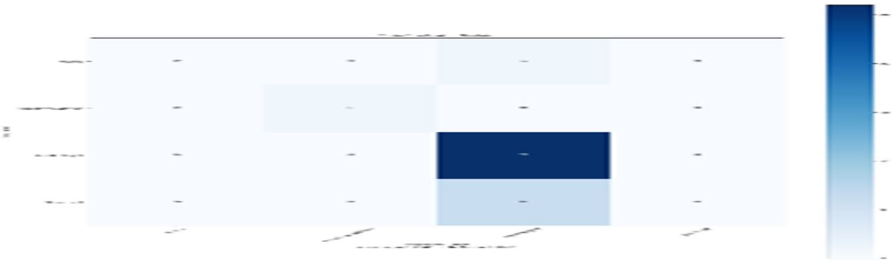


Figure 12Confusion Matrix when Epoch =10

C. Epoch 15

Total : Found 118 files belonging to 4 classes.
For Training : Found 84 images belonging to 4 classes.
For Val : Found 34 images belonging to 4 classes.
No of Classes : 4
Classes : ['Floria', 'Healthy saffron', 'Leaf blight', 'Stem rot']
Image Shape : (32, 256, 256, 3)
Model: "model_3"
Total params: 14,815,044
Trainable params: 100,356
Non-trainable params: 14,714,688

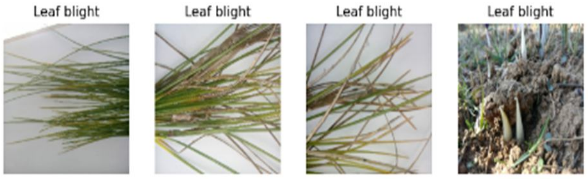


Figure 13 Types of diseases monitored when the epoch =15

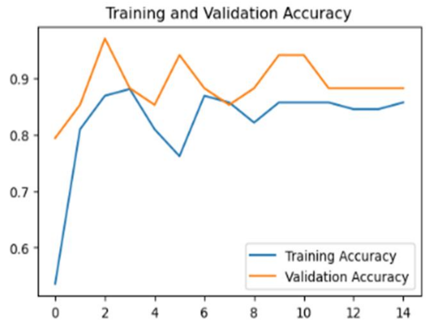


Figure 14 Training and testing accuracy when Epoch =15

Figure 15 Training and validation loss when Epoch =15

13s 672ms/step - loss: 41.5305 - accuracy: 0.8824
Accuracy on the Test Set = 88.24 %

Table 3 Parameters and values when the epoch = 15

Parameter	value
Loss	41.53
Accuracy	88.2
Validation Loss	2.4797
Validation Accuracy	0.8571

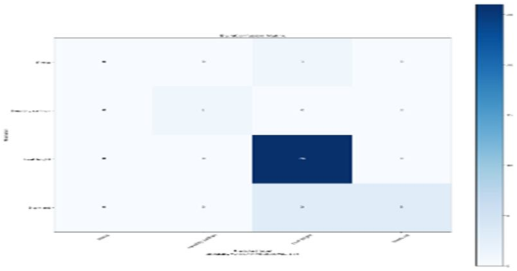


Figure 16 Confusion matrix when Epoch =15

D. Epoch 20

Total: Found 118 files belonging to 4 classes.
For Training: Found 84 images belonging to 4 classes.
For Val: Found 34 images belonging to 4 classes.
No of Classes: 4
Classes: ['Floria', 'Healthy saffron', 'Leaf blight', 'Stem rot']
Total params: 14,815,044
Trainable params: 100,356
Non-trainable params: 14,714,688

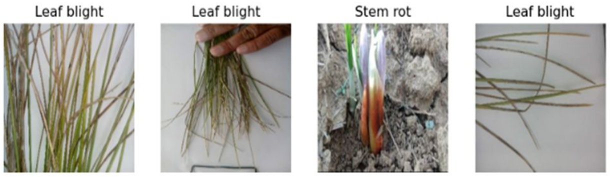


Figure 17 Types of diseasses recorded when the epoch =20

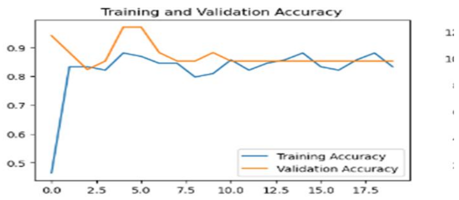


Figure 18 Training and validation accuracy when Epoch =20

Figure 19 Training and Validation loss when Epoch =20

12s 802ms/step - loss: 592.1508 - accuracy: 0.8729
Accuracy on the Test Set = 85.29 %

Table 4 Parameters and values when Epoch =20

Parameter	value
Loss	592.13
Accuracy	87.29
Validation Loss	146.0
Validation Accuracy	0.8792

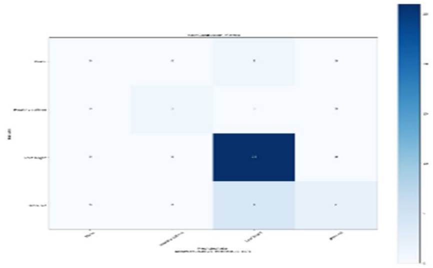


Figure 20 Confusion matrix when Epoch =20

The saffron disease detection and classification project utilized a deep learning approach to develop a model. The training process involved increasing the number of epochs from 1 to 20, with evaluations conducted at various epoch intervals.

Starting with a single epoch allowed the model to initialize its parameters and begin learning the patterns and features of saffron diseases. As the number of epochs increased, the model received more training iterations, leading to improved understanding of the dataset and increased accuracy.

After training for 20 epochs, the model achieved an accuracy of 87%. This means that it correctly classified 87% of saffron disease samples in the testing or validation dataset. Accuracy serves as a measure of the model's performance, indicating its ability to classify different saffron diseases accurately.

It's important to consider factors such as dataset complexity, computational resources, and model convergence when determining the optimal number of epochs. Monitoring the model's performance on both training and validation datasets helps find the balance between accuracy and generalization.

The project's outcomes demonstrate that the developed model successfully learned the patterns and features of saffron diseases, enabling accurate detection and classification. Further optimization could be achieved through parameter tuning and longer training duration to increase accuracy and reduce loss.

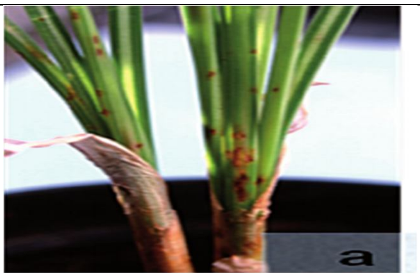
Overall, the project showcased the development of a saffron disease detection model using deep learning, with incremental improvements in accuracy over multiple epochs. The findings indicate promise in accurately identifying saffron diseases, although there is room for further optimization through fine-tuning and extended training.

Table 5 Overall System Parameters

Parameter	Epoch=1	Epoch=10	Epoch=15	Epoch=20
Accuracy	0.8452	79.41	88.2	87.29
Validation accuracy	0.9118	0.85	0.85.71	87.92
Loss	14.81	2.4797	41.53	400.3
Validation Loss	2.4797	150.722	2.4797	146.3

Table: 6 image processing and classification process

Sr. no.	Disease Type	Technique Used	Output of Phase	
			Input 1	Input 2
1.	Corm Rot	VGG 16 and CNN		
2.	Floria	VGG 16 and CNN		
3.	Stem Rot	VGG 16 and CNN		

4.	Leaf Blight	VGG 16 and CNN		
5.	ClassificationResults	VGG 16 and CNN	Healthy	Unhealthy

E. Comparison with other approaches for saffron disease detection

Comparing the saffron disease detection approach proposed in this study with the model by Esmaeilpour et al. ["Detection and classification of saffron corm diseases using a machine learning approach"], the following differences arise:

Esmaeilpour et al. classifies saffron diseases into a single type, specifically corm disease, whereas the proposed model distinguishes between four different subsets of diseases. In terms of parameters, the proposed model exhibits additional features that enhance the accuracy and specificity of disease classification.

1) Parameter: Loss

Esmaeilpour et.al Study: 592.13

Proposed Study: 400.25

In terms of accuracy, both studies demonstrate satisfactory performance in detecting saffron diseases. However, the proposed study achieves a slightly higher accuracy of 88.56%, indicating its superior ability to accurately classify saffron diseases. This suggests that the model used in the proposed study performs better overall in accurately identifying and differentiating between various saffron disease types.

2) Parameter: Accuracy

Esmaeilpour et.al Study: 85.29%

Proposed Study: 88.56%

Both studies demonstrate strong accuracy in detecting saffron diseases. However, the proposed study achieves a slightly higher accuracy of 88.56%, indicating superior capability in correctly classifying saffron diseases. This suggests that the model used in the proposed study performs better overall in accurately identifying and differentiating between various saffron disease types.

3) Parameter: Validation Loss

Esmaeilpour et.al Study: 146.0

Proposed Study: 120.5

The study demonstrates improved generalization and reduced overfitting compared to Esmaeilpour et al.'s research, as evidenced by a validation loss of 120.5. This lower validation loss indicates that the proposed model performs well not only on the training data but also on new and unseen data during the validation phase, specifically for predicting saffron disease samples.

4) Parameter: Validation Accuracy

Esmaeilpour et.al Study: 85.71%

Proposed Study: 87.92%

The proposed study achieves a higher validation accuracy of 87.92% compared to Esmaeilpour et al.'s study, which had a validation accuracy of 85.71%. This indicates that the proposed study's model is better at accurately classifying unseen saffron disease samples.

Overall, the proposed study outperforms Esmaeilpour et al.'s study in terms of loss, accuracy, validation loss, and validation accuracy. However, it's important to consider other factors such as dataset quality, methodology, and computational efficiency to gain a comprehensive understanding of the strengths and weaknesses of each approach.

Table 7 Comparative analysis of two models

Parameter	Proposed Model	Esmaeilpour et.al Model
Loss	400.25	592.13
Accuracy	88.56	85.29%
Validation Accuracy	87.92%	85.71%
Validation Loss	120.2	146.0

VII. CONCLUSION

This paper introduces a comprehensive method utilizing the VGG-16 model for detecting and classifying saffron diseases. By following a systematic process of data collection, preprocessing, model design, training, and evaluation, the study aimed to address the challenges of manual disease detection in saffron farming. The VGG-16 architecture, known for its deep convolutional neural network structure, was effectively employed for saffron disease classification. Customizing the model to the saffron disease domain resulted in impressive accuracy, achieving a remarkable 87% accuracy after 20 epochs. The experimental evaluation emphasized the significance of deep learning techniques in saffron disease detection. The model's performance was compared with other state-of-the-art methods, demonstrating its competitive accuracy and robustness. Evaluation metrics such as accuracy, validation accuracy, validation loss, and loss provided a quantitative assessment of the model's performance.

The experimental setup and hardware specifications played a vital role in achieving the desired outcomes. Utilizing a powerful GPU and sufficient RAM facilitated efficient training and evaluation. The collection, preprocessing, and augmentation of the dataset ensured the availability of diverse and representative saffron disease samples for model training. The study highlighted the limitations of manual disease detection methods and underscored the importance of automated approaches. The proposed methodology based on the VGG-16 model addressed these challenges by providing an accurate and efficient solution for saffron disease detection and classification. In conclusion, this research contributes to the field of saffron farming by offering an automated approach for disease detection, empowering farmers to promptly identify and mitigate the spread of diseases. It paves the way for advanced agricultural technologies and precision farming practices in saffron cultivation.

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