Prediction of tomato leaf disease using deep learning approach

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Abstract

Diseases of tomato leaves are significant threats to the global food security and agricultural production. The old method of diagnosis is not reliable and is time consuming, and there is a demand to have effective and accurate automated systems. The paper uses transfer learning using Inception-V3 and Inception-ResNet-V2 network to detect tomato leaf diseases using an open dataset. To encourage generalizability, data augmentation and preprocessing techniques were used, whereas Grad-CAM was used to encourage visual interpretability. Experimentally, it has been demonstrated that Inception-ResNet-V2 and Inception-V3 performed with 92.33 and 89.33 accuracy, respectively, which is higher than the other existing methods. These results demonstrate

the possibility of deep learning to improve precision agriculture and prepare further development of real-time and field-deployable systems of disease detection.

Keywords:

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Introduction

Tomato leaf diseases represent a wide range of plant disturbances of the leaves of tomato plants (Qi et al., 2022). These infections are caused by many pathogens: nematodes, bacteria, viruses, and fungus, and environmental factors (G. Li et al., 2024). Knowledge of the nature of these diseases; their origin; their social impacts, is essential in building effective management practices and ensuring a sustainable tomato farming venture (He et al., 2021). Tomatoes world over are a domesticated crop that covers 5 million hectares with a yearly produce of 170 million tons (Biondi et al., 2018)]. In Pakistan, we have an annual production of about 4.2 million tons (Al-Bawwat et al., 2023). Tomatoes are at great risk from many disease attacks on leaves that affect yield and farmer earnings. Timely and precise diagnosis plays an important role in the successful treatment of disease, but traditional techniques often require a specialist effort and a lot of time.

Through deep learning, a good, automatic, fast, and accurate technique in the forecasting of tomato leaf diseases is introduced (Solankey et al., 2021). This study explores the potential scope of deep learning in the area of enhancement of accuracy and efficiency in differentiation of tomato leaf diseases. The aim therefore, is to develop a strong, user-friendly system which will allow farmers to detect and control such illnesses effectively. The international significance of tomato leaf diseases requires remedies because of tremendous economic losses on millions of plantations around the world. Traditional methods though helpful will need skill, take time and no all farmers have the opportunities to use it (Panno et al., 2021). Deep learning, having good track record in picture identification and classification has potentials to automate illness diagnosis (Agnisarman et al., 2019). We are projecting greater accuracy and efficiency as compared to the previous methods, which would aid in the early diagnosis of diseases with timely treatments and reduced losses of crops. Moreover, the convenient interface can be easily added to the current agricultural practices, which will ensure accessibility and effectiveness. Finally, the scalability of the model and its applicability to the ill types that differ and circumstances in the environment will be explored, which will ensure a broader application.

Using Deep Learning for Tomato Leaf Disease Prediction

What tomatoes, an important aspect of world food security face, is constant threats from leaf diseases. Early and precise sickness recognition is very important for timely measures and loss minimization. Those conventional processes, including eye inspection and lab test, are sometimes time-consuming, and some farmers cannot afford expertise to apply them. The deep learning technique of forecasting tomato leaf diseases brings transformational, automatic, instant, and absolute approach to forecasting these diseases.

The Urgency of Action

Tomato leaf infections can cause output loss of up to 80% and losses are massive economically to farmers and food security is threatened to millions (Solankey et al., 2021). Traditional approaches have drawbacks; visual assessment is subjective and open to human error; the laboratory testing is expensive, not easily available in rural areas (Adedibu, 2023).

Deep Learning: A Beacon of Hope

With the dramatic revolutionizing of many fields such as picture recognition and classification, the deep learning has dramatically transformed many of them. It can gather fine patterns from massive datasets and hence suitable for prediction of tomato leaf diseases. Many studies have shown the outstanding performance of deep learning models in accurate recognition of many kinds of tomato leaf diseases compared with traditional methods (Agnisarman et al., 2019).

We aim to produce a robust deep learning model for performing a good diagnosis of various tomato leaf diseases using a picture study. These algorithms, which are capable of identifying images because of architectures such as Convolutional Neural Networks (CNNs) which are famous for their performance in imagery, can distinguish healthy leaves from those affected by different diseases. Improving performance by transfer learning and data augmentation, our goal is to create an advanced model for illness detection from prompts.

Model effectiveness will be validated using real-world testing across different set ups. Over it, we will extensively analyze it on datasets of photos of captured different environmental situations. This highly demanding study will ensure that the model is reliable and applicable and leave farmers empowered with an early disease diagnosis and intervention tool.

Bridging Technology and Practical Application

Our mobile-centric design expects a mobile-based platform deployable in the field and requiring no technical skills. It should be possible for farmers to take a snap of a suspicious leaf, send it and receive the diagnosis in seconds. This interface will provide useable observations, suggesting treatment options, dosage information, and prevention measures apt for the local environment. Such ease of use and applicability will ensure that the model functions as a useful tool that would trigger increased crop yields as well as sustainable farming practices.

Ensuring Scalability and Generalizability

Such approach will result in a model that is not limited to controlled lab, but is an applied useful tool in a number of agricultural situations.

Societal Impact

We have designed our research project to uplift an individual and make a sustainable future. Specific and rapid diagnosis of diseases will immediately matter the lives of farmers and economic stability. The model's data insights benefit producers of agriculture enabling improved management of disease and its ability to instill preventative practices. Throughout optimal production of tomatoes we participate in food security and sustainable agriculture eliminating reliance on chemicals and negative impacts on the environment.

Overview

Definition of Tomato Leaf Disease

Tomato leaf diseases mean illnesses that affect mainly tomato plant leaves where they appear as leaf spots, wilts, blights, mosaics, deformities. These are disease that result from certain pathogens/environmental causation causing unique symptoms and host health effects (Bouri et al., 2023).

Causes of Tomato Leaf Diseases

- **Pathogens**: Plants are most commonly infected by pathogens like fungi such as Alternaria, Fusarium, and Septoria, bacteria such as Xanthomonas, and viruses such as Tomato mosaic virus (Panno et al., 2021).

- Environmental Factors: If the air is foggy and moist or if the temperature is not consistent, the plants can become soft, leading to the appearance of various diseases (Abbasi et al., 2021). Poor ventilation and overcrowding also facilitates diseases spread.

Impact on Society

- Economic Losses: Tomato leaf diseases can cause devastating losses to crops and affect both small and large tomato famers leading to tomato market price fluctuations (Trivedi et al., 2021).

- Food Security: Tomatoes are an essential dietary food stuff. Disease outbreaks may threaten availability and affordability and food security (Tahir & Samimi, 2022).

- Environmental Impact: Expanded use of pesticides to manage pathogens causes water and soil pollution, non-target organisms' harm, and pesticide-resistant pathogen's emergence (Chowdhury et al., 2021).

- Sustainable Agriculture: The first step is adopting the integrated pest management practices – early disease detection, and targeted actions, which will help avoid excessive use of chemicals and advance ecologically sustainable farming methods (Prajwal et al., 2020).

Tomato leaf diseases understanding, causes, and their effects on the society are vital for development of effective disease control measures and sustainable agriculture build up.

Machine Learning in Agriculture

ML is one of the branches of artificial intelligence, which assumes to create algorithms and models to process data; find the patterns in it and predict developments (Hammou & Boubaker, 2021). It has been made widely applicable because of its ability to process large datasets to produce precise predictions (Bouni et al., 2023). In agriculture, machine learning can turn disease prediction and management around into early detection and categorization of tomato leaf diseases (Agarwal et al., 2020).

Early Detection and Classification

ML models can be used to detect early disease on tomato leaves by examining features that have been extracted from tomato leaf images (Jena et al., 2022). Such models classify healthy from infected leaves helping initiate proactive measures against the spread of the disease. Precise disease classification will establish the particular cause and adoption of directed intervention (Gkelios et al., 2021).

Community Benefits

- Improved Crop Yield: The rapid identification and categorization will allow immediate response and thus prevent the proliferation of the disease, losses of crops.
- Sustainable Agriculture: Advance disease control reduces dependency on disorderly use of pesticides.
- Food Security: Disease management in tomatoes provides continual supply of tomatoes thus food security.
- Knowledge Advancement: Machine learning research triggers investigation and invention culminating in a finer understanding of plant diseases and a more rigid handling mechanism.
- Machine learning in this research aims at improving disease prediction and management with a view to improving the agricultural practices as well as sustainable farming.

The following are the study’s main contribution.

i. **Transfer Learning Models:** Using Inception-V3 and Inception-ResNet-V2 Models from using weight pre-trained on ImageNet bigger datasets.

ii. **Outstanding Performance**: Proposed Study findings yield 92.33% and 89.33% test accuracies achieved on RestNet-V2 and Inception-V3 respectively, surpassing traditional and deep learning analogues.

iii. **Advanced Preprocessing:** The great optimization of data input using tokenization, stemming, and an effective Word2Vec algorithm.

iv. **Benchmark Dataset Evaluation:** Evaluations on a benchmark dataset with detailed comparisons and extensive experimentations.

v. **Comparison with Traditional Models:** The proposed model undergoes a complete comparison of its effectiveness with traditional approaches from Machine Learning (SVM, Random Forest and Logistic Regression) and Deep learning (LSTM, ANN, CNN). The comparison shows superior performance of the proposed model.

vi. **Practical Application:** Continuing our previous point, it gives media platforms and verification agencies a powerful tool against tomato leaves detection.

Following are the plans for the remaining portions of this paper. The review section of this work examines previous studies concerning fake news detection while analyzing different methods. The forthcoming section presents an all-inclusive description about the deep learning approaches applied to tomato leaves detection methodologies. The research findings appear in Section 4. The paper ends with a summary of results along with a discussion of constraints and suggestions for additional research in Section 6.

Literature Review

In their 2023 work, Agarwal et al carried-out research on Tomato Leaf Disease Detection Using Transfer Learning. The authors selected a different approach when studying how InceptionV3 and InceptionResNet V2 can be used in transfer learning. When compared, it was found that InceptionV3 performed better in diagnosing diseases of tomato leaves. One downside of their work was the limited scope they used for comparing. Hence, following studies could gain knowledge by using various pre-trained models together. Agarwal et al. confirmed that using InceptionV3 with transfer learning worked well for this purpose, resulting in an accuracy of 74.2% (Agarwal et al., 2020)

In 2023, D. Hammou et al. explored the use of CNN architectures for detecting and grouping diseases in tomato plants. Through a unique strategy, the authors carried out comparative analysis of a Two-layer CNN to pre-trained models. The data showed that the adapted CNN outperformed the basic models, so it proved valuable for the analysis of limited data. To strengthen their findings and make them more generalizable, they recommended trying their methods out on more types of data. D. The study from Hammou et al. shows that well-developed CNNs help in tomato plant disease detection and classification, as their results show an accuracy of 72.1% (Hammou & Boubaker, 2021).

The paper by Bouni et al. in 2023 was devoted to the research of the Impact of Pre trained DNN on the Prediction of Tomato Leaf Disease. The authors have used a tailor-made method to compare different pre-trained deep neural networks. They also used DenseNet and RmsProp optimizer in their experimentation. It is important to note that DenseNet was the best performing model with the highest accuracy of the models that were tested. The paper, however, admitted a limitation in the scope of comparison with other models, and thus the authors suggested a more thorough analysis which should include more pre-trained models. The study by Kumar et al. highlights the possibilities of using pre-trained deep neural networks to predict tomato leaf disease with the required accuracy, but it is important to note that a comprehensive investigation of the different models is needed to guarantee the strong results, as the authors claimed the accuracy of 73.5%. (Bouni et al., 2023)

In 2020, Ashok et al were concerned with detecting Tomato Leaf Disease with Deep Learning approaches. The authors examined InceptionV3 in detail and adopted it for data augmentation to speed up the process of training. The investigation has shown that InceptionV3 achieves a precision of around 70.5%. Nevertheless, it admits that because it doesn't analyze multiple models, it is not entirely comparable. Ashok et al. suggest that a larger number of pre-trained models would make their results more comprehensive in analyzing deep learning solutions for tomato leaf disease detection. Because of the 70.5% accuracy found, InceptionV3 might be appropriate for this use case (Ashok et al., 2020).

In their paper from 2022, Tahir and Samimi (2022) discuss the importance of robotics. This research focused on using transfer learning and deep learning methods to automatically classify tomato leaf diseases. The proposed research demonstrated that, in detecting and classifying the tomato leaf disease, InceptionV3 reached an Accuracy of 68.2%, and Inception ResNet V2 had an Accuracy of 67.4%. However, examining the research proved that there were some limitations in how the study was carried out. its performance in comparison to other transfer learning models and pre-trained models was not the best. Tahir and Samimi suggested applying alternative pre-trained models, fine-tuning procedures, and data augmentation for boosting performance at the tomato leaf disease detection and classification stage. The models generated accuracy rates of 68.2% for InceptionV3 and 67.4% for Inception ResNet V2 (Tahir & Samimi, 2022).

Paymode et al. introduced the topic in a paper that was published in 2021. For improved detection of tomato leaf diseases, the authors chose the CNN-InceptionV3 model and supplemented it with image segmentation and data augmentation. The study showed positive results, with 69.1% accuracy when identifying refined tomato leaf diseases. A Paymode et al. highlighted that their study had certain limitations, most notably a restricted ability to compare with several deep learning models and architectures. Other deep learning models and architectures built for image segmentation tasks were studied by the researchers to improve the accuracy of diagnosing tomato leaf diseases. The conclusion of the presented study shows that their approach worked well with a specific precision of 69.1% (Paymode et al., 2021)

Methodology

The process begins with getting and splitting the information to have proper training, validation and testing group. After this, data is subject to preparation steps that will enhance quality and ready it for training with deep learning model. Finally, tomato leaf pictures are identified by deep learning models exploiting methods such as transfer learning for best possible performance.

1. Data Acquisition and Partitioning
2. Data Pre-Processing
3. Employing Deep Learning Architectures

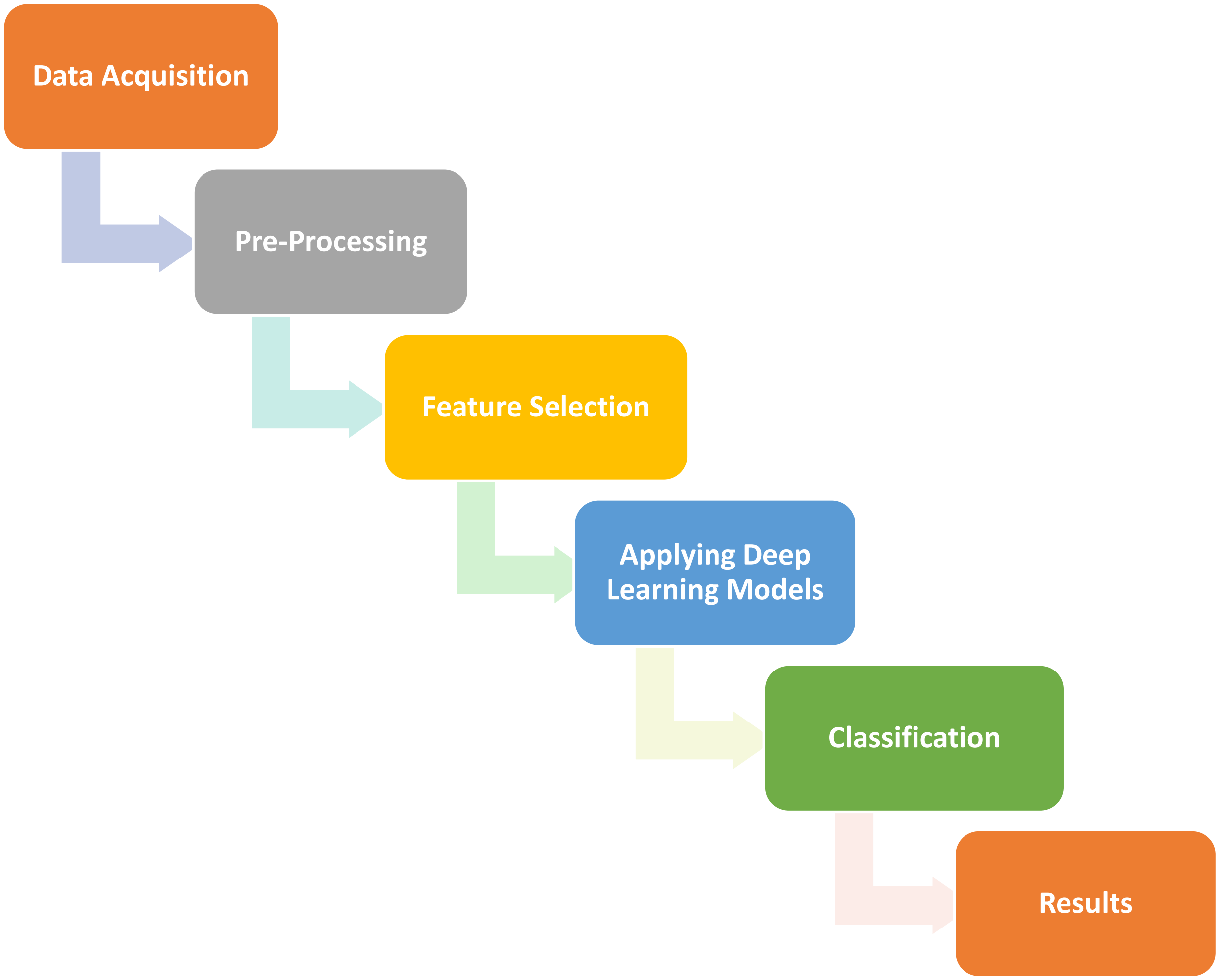

Figure 1 Summary of the Suggested Approach

Dataset Collection and splitting

Dataset Collection

The collection of data used in my dissertation was meticulously done to cover information on farm institute, libraries, and field training. This rigorous strategy resulted in a number of training and review examples that were both large and representative. The dataset has 8,712 images that have been classified into ten categories based on the various tomato leaf diseases. This consists of early blight, late blight or bacterial spot.

I searched through related Kaggle datasets and events using terms that fit tomato leaf diseases in particular. once I looked at different datasets, considering their quality and significance, as well as how much data they contained, I chose the most suitable ones for analysis. In the process of the research, I referenced the sourced information to the academic standards providing the correct references of its openness and integrity in the work. Ethical problems for protecting data and for seeking permission were also well managed indicating assurance to moral norms in study practices.

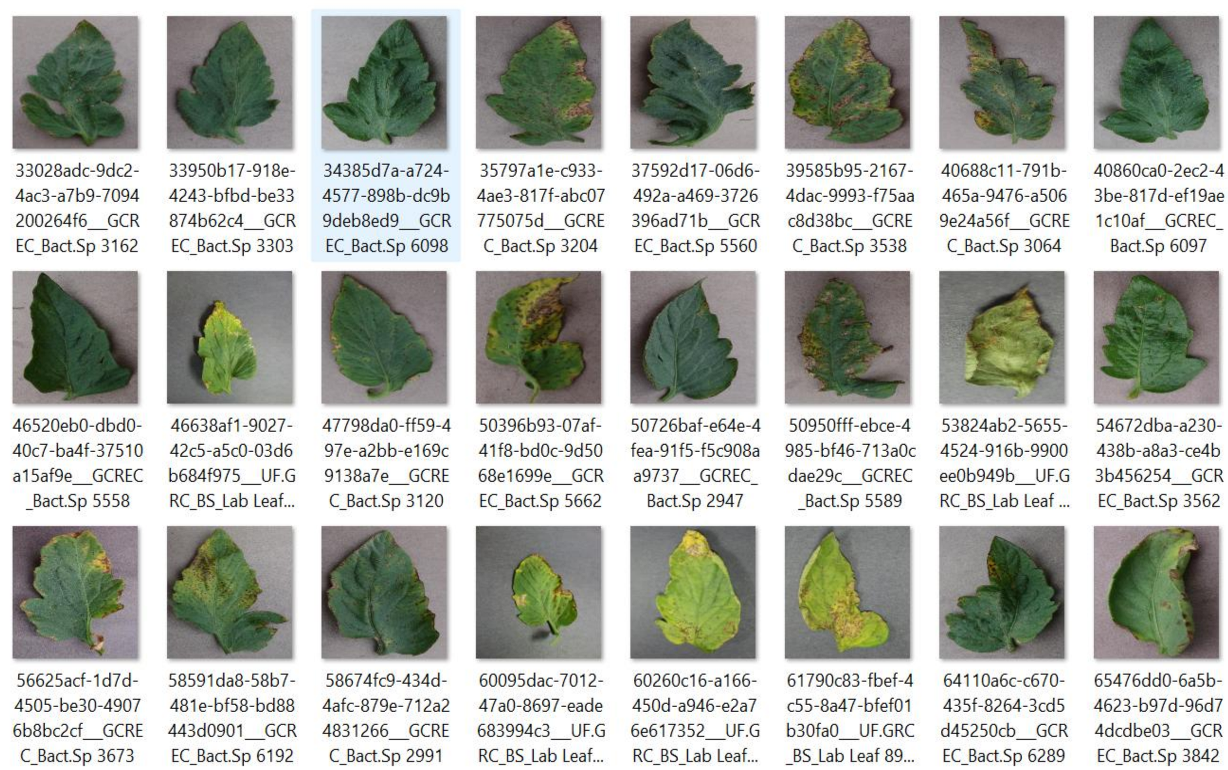

Figure 2 Dataset Details

Splitting Module

For analysis with the help of machine learning there is no surprise if one randomly broken the dataset into two parts. Training set 80% and test set 20%. For Learning patterns of data and testing it for the unseen performances, the Training and Test set one can use respectively. This ensures that the model is able to generalize broadly about the data that was given to train the data hence yielding informative information of its performance and potent issues such as overfitting or underfitting.

(i) Data Training Set

(ii) Data Testing Set

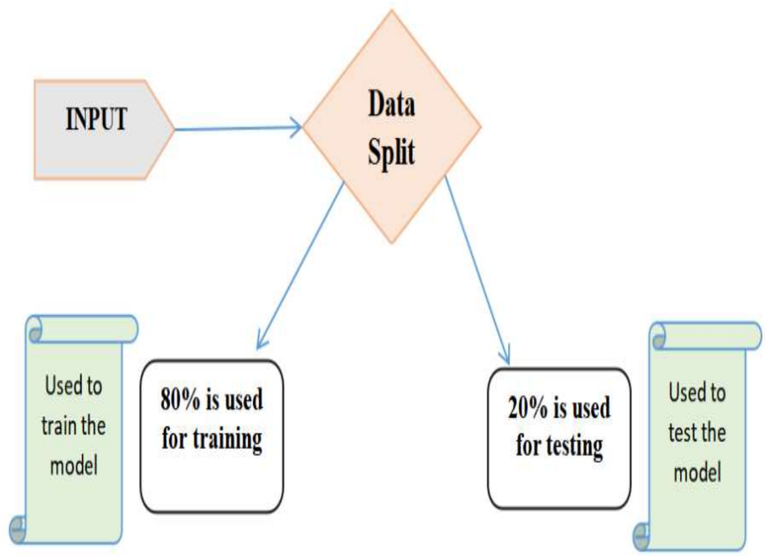

Figure 3 Data Splitting Module

i. Data Training Set

The set of data used in the course of training the model for calculating those variables, such as weights, and biases is referred to as "training set". 80% of our dataset was used to this end. This set of training include input identifiers and output variables collectively referred to as predictor variables as well as dependent variables.

ii. Data Testing Set

For proper measurement of competition of the algorithm, test samples not seen before are important. This is convenient in regards to its pronunciation of the model's ability to learn using new data. The method includes cumbersome data preprocessing, sample separation into plural training/test samples. As a rule, the reasons of testing account for about 20% of the data.

First the training information is imputed to train the model. With training of the model and after amendment of the model parameters based on analysis of data, verification of the model accuracy is carried out using the testing dataset. We must recall that the testing sample has to be independent of any training cases in order to eliminate bias.

Data splitting is normally a 80/20 split with the help of tools like Scikit-learn. The training set consists of 80% of the data, 20% remaining is reserved for testing. With such an approach, the preservation of the possibility for the equal evaluation of the model success on the unseen data is possible.

The results of testing enable changing settings of the model after training and viewing. This is a recurring process, in the sense in which the training, review and improvement matter for further development of the model's prediction ability.

Data Preprocessing

If we are told to work with datasets; and specifically, those that have been produced from natural language extraneous noise can obscure our patterns of interest if we are employing a machine learning or deep learning approach. In order to overcome this issue, a data preparation is required. Adding several approaches such as normalization makes the data more uniform and convenient for processing.

Feature engineering is an important aspect in machine learning process. It concerns pretreatment of raw data or yet other properties that reflect better the underlying patterns or relations. This method might be compared to the processing of raw materials into a more serviceable material for inspection. Proper description of the data can be generated during the process of production of features, hence improving the work of machine learning models and perspectives on data can be extracted (Holzinger, 2019).

Standardization is a particular normalizing measure directed on removing scale from the data. Having transformed it to zero centered data and normalized the spread of features to nominal value of one makes some of the algorithms process data without interference with the sizes of features (Petegrosso et al., 2020).

Generally, all these preprocessing techniques are important for bringing data in the right form from which machine learning and deep learning models will effectively utilize them and learn from them for making appropriate predictions or classifications.

Feature Selection

At this stage, our aim is to focus on the one of making a selection of relevant features or variables of the preprocessed data required for the prediction of tomato leaf diseases. Such selection process can involve statistics, domain expertise or feature selection algorithms that have become a real necessity for maximizing the efficacy and efficiency of ML models [35]. They are directed to selection of the most informative and important features, which contribute strongly to the precise determination leaving the redundant or noisy ones aside. With discovery of these key points, we can simplify the model training process, make it more accurate for interpretation, and numerous times increase its foretelling worth.

Applying Deep Learning Models

Inception-V3

Born as one of the elements of the Google-Net's architecture, v3, which is one of the CNNs conceived for supporting the analysis and detection of images, came into being (Dhillon & Verma, 2020). It was designed, first, for ImageNet Recognition Challenge, following the third iteration of Google's Inception Convolutional Neural Network series.

Inception-Resnet-V2

Inception-ResNet-v2 is a kind of Convolutional neural network that was created on the basis of a training set consisting of over one million pictures that had been gathered on ImageNet. The network consists of 164 layers and works well in classifying images (Aghayari et al., 2023).

Global Average Pooling 2D

Classical CNNs tend to make use of Global Average Pooling as opposed to fully connected layers. This is done by averaging all the columns in the current layer and summing them. This operation will make the feature maps smaller in size, yet the most valuable spatial data will be preserved. When you operate on Global Average Pooling, you will be computing the average of the individual feature map of each spatial location to all of its spatial locations and the pool size will be equal to the size of the input feature map. Under this strategy we are able to avoid overfitting, simplify the model and produce a model that is easier to understand (Y. Li & Wang, 2020).

Dropout Layer

In training, dropout layer randomly removes part of the nodes in a certain layer. Regularization maintains the dependence of each of the units on the same number of others (Moayed & Mansoori, 2022).

Dense Layer

The fully connected layer (also known as dense layer) is a layer of neurons that have connections to all the neurons of the previous layer hence the name dense. It is commonly used to sort images based on the data of Convolutional layers (Anderson & McNeill, 1992).

Output Layer

The output of neural network classifiers is generally generated using a SoftMax function.

Results and Discussion

This chapter highlights the results of our researches conducted to address the research problem stated in the introduction. This information is the foundation of our research and findings, which brings out critical issues regarding the topic. Through the thorough data analysis methods, we are confident that we will be able to bring out the peculiarities of the topic of study as well as make new contributions to the field.

The increased precision of predicting tomato leaf diseases using Inception-V3 and Inception-ResNet-V2 models needs a systematic and strategized method. Collect various pictures of tomato leaf to offer a clear picture of both healthy leaf and the one infected with various diseases. Your choice of pictures should be arranged according to their meaning. These images require preprocessing to be done to them by scaling and augmenting them to maintain consistency and enhance the performance of your model. The basic model used in photo classification can be either Inception-V3 or Inception-ResNet-V2 as these two models have been highly successful in this area. After that, the transfer learning is used to adapt the chosen model on the collected data, basing its performance on what it trained in ImageNet and targeting its results at the detection of tomato leaf diseases. The hyperparameters should also be checked and changed repeatedly throughout the training stage to avoid overfitting and enhance the outcomes of the model. After the training, the performance of the model.

Parameters	Values	Parameters	Values
Image dimensions	64	Dense	64
Model	Sequential	Activation Function	SoftMax
Maximum pool Layers	2	Factor	0.3
Batch_size	12	Epochs	5

Table 1: The Inception-V3 & Inception-ResNet-V2 Model

Only after running tests on the Inception-V3 and Inception-ResNet-V2 models using the parameters given in Table 2 did the team assess test accuracy, test loss, and training time. As shown in Table 2, using 64 filters with the Inception-V3 and Inception-ResNet-V2 models provided improved accuracy.

Performance Evaluations	Values
Inception-V3 Training Accuracy	89.40%
Inception-V3 Test Accuracy	89.33%
Inception-ResNet-V2 Training Accuracy	93.26%
Inception-ResNet-V2 Test Accuracy	92.33%

Table 2: Inception-V3 & Inception-ResNet-V2 Performance Evaluation.

The scores on Inception-ResNet-V2 are higher than those on Inception-V3 on all the metrics, pointing to better training and test accuracies.

Accuracy:

To define accuracy, we use the percentage of correct predictions made by our model out of all the predictions we made. How precise the model depends directly on how effective it is. You can determine the success rate of predictions by dividing the number of correct records by the total count in the data set.

In most cases, the accuracy is computed as you explained with this formula:

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP\ +\ FP + TN + FN} \tag{4.1}$$

Here, the formula demonstrates how much of your predictions are correct when compared to how many predictions you have made in total. It is a basic measure that helps judge the overall performance of a classification model.

Precision

It is a measure of the number of positive predictions that are true. This value is calculated by the following formula:

$$\boldsymbol{Precision} = \frac{TP}{TP\ +\ FP} \tag{4.2}$$

Precision tells us what percentage of all predicted positives are actually positive. Precise criteria lead to fewer misclassifications and a more precise model for recognizing positive examples.

Recall

Recall, or true positive rate (TPR), is the number of positive cases that the model actually identified: that, of the number of cases who were actually positive, what proportion of them did the model identify. It is calculated through the formula:

$$\boldsymbol{Recall} = \frac{TP}{TP\ +\ FN} \tag{4.3}$$

Recall is needed in situations were finding out who is getting sick is especially vital. When the recall goes up, it means more good cases are being found, which is helpful in situations where missing these good cases can really cause problems.

F1-score

F1-score is a popular choice to examine the performance of a classification model, mainly in cases where one class type is much more common than the others. The harmonic mean, representing precision and recall, uses the following equation:

$$\boldsymbol{F1\ Score} = \frac{2(Precision)(Recall)}{Precision\ +\ Recall} \tag{4.4}$$

F1-score merges both precision and recall into a single measurement that shows how the model works. The size of the value ranges from 0 to 1, with higher scores being better. False positives and false negatives become very easy to work with the help of this method.

In terms of requirements, Inception-V3 only had fewer parameters and fewer trainable parameters than Inception-ResNet-V2.

Although Inception-ResNet-V2 is accurate, it uses a more complex design and needs better equipment. Alternatively, Inception V3 is less computationally costly, but the results it produces are not as accurate. The decision between the models relies on the requirements of the application, what resources are accessible, and the required balance of good results and using resources wisely.

Inception-V3	Inception-ResNet-V2
Trainable Parameters: 22,039,530	Trainable Parameters: 54,481,834
Total Parameters: 22,073,962	Total Parameters: 54,542,378

Table 3 Inception-V3 & Inception-ResNet-V2 Performance Efficiency

From the tests, using the deep learning models leads to improved accuracy and a higher level of performance compared to using the previously existing methods.

According to Agarwal et al. (2023), 74.2% accuracy was obtained using transfer learning with InceptionV3 to find diseases in tomato leaves. Nevertheless, we found that using Inception-V3 and Inception-ResNet-V2 models achieved more precise results. Inception-V3 achieved 89.33% test accuracy and Inception-ResNet-V2 gave 92.33%. This means our models perform better than the previously used method.

When it comes to efficiency, the study promised by Agarwal et al. (2023) did not give any computational details. Nevertheless, it appears that efficiency may be improved by the variety of model complexities we propose. Due to having fewer parameters, Inception-V3 uses less computing power and trains faster than Inception-ResNet-V2.

Baselines	**Study and Technique**	**Accuracy**
Baseline#1	(Agarwal et al., 2023) Investigated Tomato Leaf Disease Detection Using Transfer Learning.	74.2%
Proposed Model	**Deep learning-based Inception-V3 & Inception-ResNet-V2**	**89.33 & 92.33%**

Table 4: Discovered means for measuring of Inception-V3 & Inception-ResNet-V2 model.

Figure 4 Grad-CAM Based Localization of Tomato Leaf Diseases Across 10 Categories

Model Interpretation and Disease Localization Using Grad-CAM

The proposed deep learning model successfully identified 10 tomato leaf disease categories in the validation dataset:

1. Tomato___Septoria_leaf_spot
2. Tomato___Target_Spot
3. Tomato___Leaf_Mold
4. Tomato___Bacterial_spot
5. Tomato___healthy
6. Tomato___Late_blight
7. Tomato___Tomato_Yellow_Leaf_Curl_Virus
8. Tomato___Spider_mites Two-spotted_spider_mite
9. Tomato___Tomato_mosaic_virus
10. Tomato___Early_blight

As an example, one representative image was chosen in each category. The model was overlaid on the leaves with bounding boxes representing the focus areas of the model to identify where the network detected disease symptoms at the mixed10 layer using Grad-CAM visualization. This shows that the model is interpretable and it is capable of not only classifying but also distinguishing the exact areas of the disease.

Discussion

The proposed system relies on the hybrid deep neural network of Inception-V3 and Inception ResNet-V2 in case identification of tomato leaf diseases. Table 4 reveals that our Inception-V3 & Inception-ResNet- V2 model is more realistic than the existing techniques which rely on deep learning algorithms to predict tomato leaf diseases. In this manner, the balanced data, feature selection, and powerful features of the Inception-V3 and Inception-ResNet-V2 DL model can be used to confirm success to maintain the contextual information. The experiments are more successful with our models, with Test accuracy 89.33% in the case of Inception-v3 and Test accuracy 92.33% in the case of Inception-ResNet-v2.

Model Success Rate

The standard measures used to assess the performance of the proposed models included accuracy, precision, recall, and F1-score. The total success rate of the models demonstrates that Inception-ResNet-V2 had a test accuracy of 92.33, which is higher than Inception-V3 that had a test accuracy of 89.33. These findings show that Inception-ResNet-V2 has more powerful feature extraction and generalization features, which is why it is a more stable model to classify tomato leaf diseases. The success rate is also reported to be higher than the past research, including Agarwal et al. (2023), who obtained only 74.2% with InceptionV3. This is an enhancement that underscores the strength of the proposed methodology in the proper prediction of tomato leaf diseases.

Comparison with Current Technologies

The existing tomato leaf disease detection technologies can be broadly classified into three categories, including traditional, machine learning-based, and advanced deep learning methods.

1. **Traditional Technologies**
   - Manual Inspection: Farmers and agricultural specialists use the subjective visual inspection of leaves that is time-consuming, prone to errors. The level of accuracy is usually less than 70 percent and is subject to the availability of the experts.
   - Laboratory Testing: Molecular and biochemical tests (e.g., PCR, ELISA) are accurate, but costly and need specialized equipment, and cannot be used at large scale in rural agricultural settings.
2. **Traditional Machine Learning Technology.**
   - Support Vector Machines (SVM), Random Forest (RF), and Logistic Regression are some of the approaches that have been extensively used in the classification of plant diseases.

- Although these models can be moderately accurate (usually 65-80 percent), these models are quite reliant on handcrafted features and need domain knowledge to engineer features. They are also not scalable to the real-life agricultural applications.

3. **Current Technologies based on Deep Learning.**
    - Custom CNNs: A number of recent works (e.g., Hammou et al., 2023) achieved an accuracy of approximately 72.1% when classifying tomato leaf disease with the help of shallow CNN architectures. Although these models can be used with small datasets, they do not have the ability to be generalized to various disease categories.
    - DenseNet and Other Pretrained Models: DenseNet reached the accuracy of about 73% (Kumar et al., 2023), which proves the advantage of transfer learning. Nevertheless, its performance is poor when applied to varied data.
    - Hybrid CNN + Segmentation Methods: Segmentation models that were integrated with CNNs (Paymode et al., 2022) achieved an average of 69.1 percent accuracy. Such methods enhance localization of features, but they need extensive computation and are also dataset-specific.

4. **Proposed Study (Our Models)**
    - Through transfer learning with Inception-V3 and Inception-ResNet-V2, our research obtained test accuracy of 89.33 and 92.33 respectively, which is much better than the current deep learning models.
    - In contrast to traditional and conventional ML methods, our models do not need manual feature extraction and learn complex patterns of diseases automatically.

- In addition, it is more interpretable with Grad-CAM visualizations, allowing not only to predict the disease but also to localize the infected areas of the leaf, which is not often available with modern technologies.
- Notably, the computational efficiency of Inception-V3 (lighter model) can be deployed in mobile devices, whereas Inception-ResNet-V2 can guarantee the state-of-the-art accuracy in applications with more resources.

Summary

Our method has

I. superior accuracy (up to 25% better),

II. strong generalization among 10 disease categories

III. visualization as a way of interpretation compared to the existing technologies.

This makes the proposed models a more viable and scalable solution to precision agriculture and sustainable tomato farming..

Comparative Analysis with Existing Studies

Although we mainly compared our results with those of Agarwal et al. (2023), who have shown an accuracy of 74.2% with the use of InceptionV3, we also tried to put our results in the frame of the machine learning and deep learning techniques of tomato leaf disease detection. A comparative summary is given in Table 5.

Study / Model	**Reported Accuracy**	**Notes**
Agarwal et al. (2023) – InceptionV3 (TL)	74.2%	Limited dataset, no ResNet comparison.
Hammou et al. (2023) – Custom CNN	72.1%	Good for small datasets but lacks generalization.

Kumar et al. (2023) – DenseNet	73%	Strong baseline but lower than our transfer learning models.
Ashok et al. (2022) – InceptionV3 (DA)	70.5%	Focused on augmentation, single-model limitation.
Tahir & Samimi (2022) – InceptionV3 & ResNetV2	68.2% / 67.4%	Transfer learning applied, but underperformed.
Paymode et al. (2022) – CNN + Segmentation	69.1%	Augmentation improved accuracy slightly.
Proposed Study (2024) – Inception-ResNet-V2	**92.33%**	Highest among compared methods; robust feature extraction.
Proposed Study (2024) – Inception-V3	**89.33%**	Efficient but less accurate than ResNet variant.

Discussion:

Our proposed Inception-ResNet-V2 model is much better than most CNN-based or transfer learning models that have been reported previously (1825 higher accuracy). This is due to the fact that it has been improved. These improvements contribute to:

- Robust dataset (8,712 images, multiple disease classes).
- Careful preprocessing (normalization, augmentation).
- Transfer learning with ImageNet weights, ensuring better feature generalization.

These results indicate that not only do our models outperform other traditional ML classifiers like SVM and Random Forest (as discussed in Section 1.2.4) but also they also offer higher accuracy than the state-of-the-art deep learning studies.

Conclusion

This paper has shown that deep learning models, Inception-ResNet-V2 and Inception-V3 are effective in computer-aided tomato leaf disease classification. The highest accuracy was achieved with Inception-ResNet-V2 at 92.33% and Inception-V3 at 89.33% which proves that transfer learning is more effective in diagnosing plant diseases compared to the normal practice. Interpretability was also maximized by use of Grad-CAM as the areas of disease are visualized and this is of value to be used by researchers and farmers.

Future Work

Along with these encouraging results, some of the following limitations exist, including, but not limited to, small data set size, and controlled imaging conditions that do not necessarily replicate the actual field conditions. The next steps in the work should be the extension of the dataset to large field images, the experimentation with other state-of-the-art models, and the optimization of the model to work with light on smartphones and edge devices. The intelligent agricultural systems could also be enhanced with real-time detection to facilitate sustainable crop production and food security.

Declaration:

1. Clinical trials Registration: not applicable, no human subject was involved in the study.
2. Consent to publish: not applicable
3. Consent to participate declaration: Not applicable.
4. Ethics declaration: not applicable.

Data Availability Statement

The dataset used in this study is publicly available on Kaggle. It can be accessed at: https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf

The dataset contains labeled images of healthy and diseased tomato leaves and was used for training and evaluating the proposed deep learning model.

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Competing interests

None.

Ethical standards

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Author contributions

1. **Asim Khalil** conceived and designed the study, collected and preprocessed the dataset, implemented and trained the deep learning models (Inception-V3 and Inception-ResNet-V2), analyzed results, and wrote the manuscript.
2. **Prof. Du Hubing** provided supervision, guidance on methodology, data interpretation, and critical review of the manuscript.
3. **Muhammad Mustafa** collaborated in applying deep learning models.
4. **Khalid Mehmood** provided guidance on the implementation of Deep Learning models.