**Tomato Plant Leaf Disease Detection using CNN**

**A PROJECT REPORT**

***Submitted by***

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***in partial fulfillment for the award of the degree***

***of***

**Bachelors Of Computer Applications**

**IN**

**Artificial Intelligence and Internet of Things**

**The ICFAI University**

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**IcfaiTech**

**July 2023**

**BONAFIDE CERTIFICATE**

Certified that this project report “**Tomato Plant Leaf Disease Detection using CNN” i**s the bonafide work of **“Ayush Bhosle”** who carried out the project under my supervision.

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**ABSTRACT**

This project focuses on the development and evaluation of a Convolutional Neural Network (CNN) model for image classification. The objective of the project is to create a model capable of accurately categorizing images into predefined classes. The project utilizes a dataset of preprocessed images and employs TensorFlow and Keras libraries for model construction and training.

The background of the project lies in the increasing importance of computer vision applications and the need for efficient and accurate image classification techniques. To address this, a CNN architecture is designed, comprising multiple convolutional and pooling layers followed by fully connected layers. The model is trained using a combination of data augmentation and preprocessing techniques to enhance its generalization capabilities.

The project workflow involves splitting the dataset into training, validation, and test sets, with a focus on ensuring data integrity and sufficient variety in each set. The training process is monitored using an Early Stopping callback to prevent overfitting and to achieve optimal performance.

Upon completion of training, the model's performance is evaluated using various metrics such as accuracy, F1 score, precision, and recall. The classification report provides a comprehensive overview of the model's effectiveness in categorizing images across different classes. A heatmap-based confusion matrix visually represents the model's performance in handling different classes.

The results demonstrate the model's ability to accurately classify images and its effectiveness in distinguishing between classes. The project emphasizes the importance of a well-structured CNN architecture and appropriate training techniques in achieving high-quality results in image classification tasks.

The project concludes by discussing the significance of the achieved results and the potential applications of the developed model in real-world scenarios. The abstract encapsulates the project's main objectives, methodologies, and outcomes, offering readers a concise understanding of the project's scope and achievements.

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**1. Introduction**

Identifying plant diseases from leaf images is a crucial focus in precision agriculture, benefiting from advancements in computing power, image processing, and the latest research in Neural Networks. Various artificial intelligence (AI) approaches, including Neural Networks, Logistic Regressions, Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Naïve Bayes, and Deep Convolutional Neural Networks (Deep CNN), are commonly employed for the detection and classification of plant diseases.

Rumpf et al. [4] showcased the use of SVMs in identifying three diseases in sugar beet roots through leaf images, while Mokhtar et al. [3] utilized SVM for the classification of two types of tomato plant diseases with a reported accuracy of 92%. Johannes et al. [5] applied the Naive Bayes technique to identify three diseases affecting wheat leaves. In a comprehensive evaluation by Yang and Guo [8], various Machine Learning techniques, including Naïve Bayes, SVM, K-Means clustering, Artificial Neural Networks (ANN), Decision Trees, and Random Forests, were reviewed for the identification of plant diseases from leaf images. This study also integrated machine learning for identifying genes involved in plant-pathogen interactions.

Recent research emphasizes Deep Learning as a superior approach for achieving high accuracy in plant disease identification [6, 9, 10]. Transfer learning on pre-trained models from other domains has become a common practice, yielding favourable results in disease classification.

Convolutional Neural Networks (CNN) stand out as the predominant deep learning method for analyzing image data. Mohanty et al. [6] utilized popular CNN models such as AlexNet and GoogLeNet for predicting classes of plants and diseases in images from the PlantVillage dataset [13]. Ferentinos [10] demonstrated the use of pre-trained models, namely Alexnet and VGG, for classifying plants and diseases across 25 different plants and 58 distinct crop and disease classes. While reporting an impressive 99.53% accuracy with the VGG pre-trained model on the augmented PlantVillage dataset, the authors noted significantly lower accuracy for images from a different database.

Zhang et al. [14] applied transfer learning to identify maize leaf diseases across 9 types of maize leaves. Employing max-max-ave pooling in three CNN hidden layers, the authors achieved an accuracy of 98.9% for GoogleLeNet and 98.8% for Cifar10 neural networks. Rangarajan et al. [9] utilized transfer learning with AlexNet and VGG16 to train and classify tomato plant disease images from the PlantVillage dataset, reporting approximately 97.29% accuracy for AlexNet and 97.49% for VGG16 on 373 test images in each class.

Fuentes et al. [15] proposed Region-based CNN (R-CNN) and Region-based FCN (R-FCN) for identifying diseases and bounding boxes in tomato leaves images. The authors manually annotated diseased portions, applied augmentation to prevent overfitting, and used pre-trained models VGG and ResNet for their CNN design. They achieved a best mean accuracy of 83.06% for R-CNN and 85.98% for R-FCN.

In the realm of plant disease identification, many authors resort to using pre-trained models from other domains and applying transfer learning for their specific tasks. Despite attempts to simultaneously identify diseases in multiple crops [6, 10], it's noteworthy that pre-trained models are often designed for scenarios with a large number of classes, which contrasts with the relatively small number of classes in plant diseases. Some efforts have been made to develop low-order CNN models for plant disease identification [18, 19, 20], but reported accuracies remain modest.

This paper introduces a lightweight CNN model for identifying nine types of diseases in tomato plants. Unlike complex pre-trained models with numerous hidden layers and parameters, the proposed CNN model prioritizes reduced storage capacity and fast response without compromising accuracy. Notably, the model exhibits strong performance in comparison to standard Machine Learning approaches and popular pre-trained CNN models. The model's robustness is demonstrated by its excellent performance on a distinct dataset of tomato crops. Additionally, the paper presents a novel augmentation method, creating new leaf images under varied lighting conditions to simulate real-world scenarios influenced by sunlight position and leaf shadows.

This paper conducts a comparative analysis between the proposed CNN model, traditional Machine Learning (ML) techniques, and pre-trained CNN models. The findings demonstrate that the proposed CNN model achieves comparable accuracy while requiring significantly less storage space. The key contributions of this paper include the improved performance of the proposed CNN model over pre-trained models, superior results compared to traditional Machine Learning methods, state-of-the-art accuracy, and robust performance on diverse datasets.

The structure of the paper is organized as follows: Section 2 provides a brief overview of traditional machine learning methods and deep convolutional neural networks. In Section 3, the proposed CNN model is detailed. The dataset utilized in this study is outlined in Section 4. Experimental results and analysis are presented in detail in Section 5. Section 6 discusses the main findings of the research, followed by conclusions in Section 7.

**2. Materials and Methods**

* 1. *. Dataset of Tomato Leaf Images:*

Mendeley (data.mendeley.com) [1] is a publicly available dataset which contains 14,531 images of diseased and healthy tomato plant leaves collected under controlled conditions, with each image size of 256\*256 to 227\*227. We analyzed these images of tomato leaves, which have a spread of the following class labels assigned to them: Bacterial spot, Early blight, Healthy, Late blight, Leaf Mold, Septoria leaf spot, Target Spot, Tomato mosaic virus, Tomato yellow leaf curl virus, Two-spotted spider mite.

Appendix A.3 shows samples from the dataset for a better understanding of the classification.

* 1. *Image Pre-processing:*

The principal objective of image enhancement is to process an image for a specific task so that the processed image is better viewed than the original image and the model can accept the format of images. Pre-processing includes resizing, reshaping and many other techniques for converting image in a model acceptable format. Figure 2.1(A) shows the code used for applying these methods. A good starting point to preprocess and normalize the pixel values involves first converting the data type from unsigned integers to floats, and then dividing the pixel values by the maximum value (i.e.,255).

A simpler way of preprocessing the pixel values to normalize the data using a built-in function of keras called as resize and rescaling. We can create a variable to use later while feeding images to the model. The following method was applied to each image of the dataset later:

* 1. *TensorFlow:*

TensorFlow, developed by Google's Brain team, is an open-source machine learning framework that has gained immense popularity since its launch in 2015 [6]. Widely used in artificial intelligence and deep learning, TensorFlow offers a flexible and efficient platform for creating, training, and deploying machine learning models. With its core concept centered around computational graphs, TensorFlow enables users to design complex models using interconnected nodes to represent operations. These operations can be executed across different hardware devices, optimizing performance and resource utilization.

TensorFlow's key features include adaptability across various machine learning tasks, user-friendly APIs like Keras, scalability for both small experiments and large-scale deployments, visualization capabilities through TensorBoard, and a strong community of developers and researchers.

* 1. *Dataset Partitioning:*

A function is used to segregate the dataset into 3 sections for the purpose of implementing and testing the model. The splitting was done as follows:

Training Set: The proportion of data for training was set to 80% of the total dataset

Validation Set: The proportion of data for validation was set to 10%

Test Set: The proportion of data for test was set to 10%

We used shuffle parameter to shuffle the dataset using a shuffle buffer of size 1000 with a fixed random seed (12).

The train set is created by taking the first ‘train size’samples from the shuffled or origional dataset, while validation and test datasets are created by skipping the training samples and then taking the next ‘validation size’ and ‘test size’ samples respectively.

*2.5 Data Augmentation:*

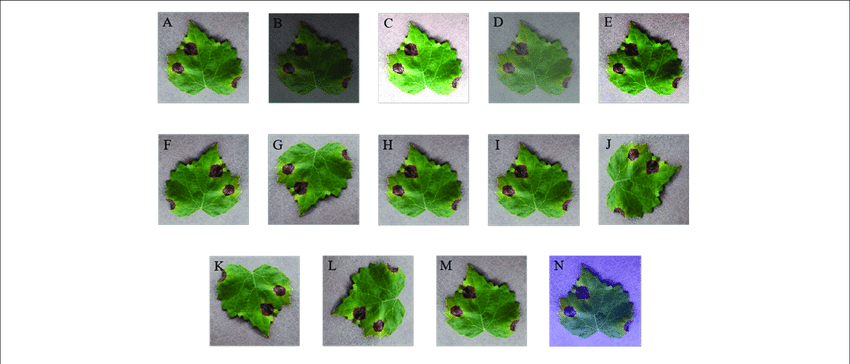
Data augmentation is a technique used to artificially expand the diversity of a dataset by applying various transformations to the existing images. This augmentation enriches the dataset with variations of the original images, enhancing the model's ability to generalize and perform well on unseen data (Shorten & Khoshgoftaar, 2019) [7]. By exposing the model to a wider array of data instances, data augmentation helps prevent overfitting and allows the model to learn more robust and flexible representations (Perez & Wang, 2017) [8].

In this project, data augmentation played a pivotal role in enhancing the training process of the Convolutional Neural Network (CNN) model. Random horizontal and vertical flips were applied to images, introducing variations in orientations and reflections. Additionally, slight random rotations were introduced, simulating natural variations in image alignment and further increasing the dataset's diversity.

Through the incorporation of data augmentation during the training phase, the CNN model was able to learn patterns and features from different viewpoints and orientations. This exposure to augmented data contributed to a model that was more resilient to real-world variations and capable of performing well on a broader range of inputs. The model's enhanced generalization was particularly beneficial when dealing with novel, unseen data.

Data augmentation serves as a powerful strategy to overcome the limitations of a limited dataset, which is a common challenge in machine learning. By generating additional training examples through augmentation, the model's performance is improved without the need for collecting substantial amounts of new data (Shorten & Khoshgoftaar, 2019) [7]. This efficient utilization of existing data demonstrates the potential of machine learning techniques to adapt and excel even with constrained resources.

Figure 1 shows visual representation of how Data Augmentation is applied on a sample leaf image. [5]



***Figure 1:*** *Data Augmentation by brightness, rotations etc.*

**3. Model**

*3.1 Architecture:*

The CNN architecture implemented for the task of image recognition of Tomato Plant Leaf using the Mendeley Dataset [1] is presented in Table 3.1(a). The first four layers of the model apply the convolutional operation to the input image (by sliding over the image first vertically and then horizontally). Note that while the size of filter is selected by the model is equal to 3, which is standard choice, the stride size is set to 2. This choice is based on two considerations. First choosing a stride equal to 2 let us downsample the image smartly, making the architecture more expensive than the equal one using pooling layers to downsample [2]. In particular, by using a convolutional layer instead of a pooling layer the CNN is capable to learn certain properties that are lost by the latter. This is due to the fact that pooling is a fixed operation, while convolution can be learned. The down side is that this choise also increases the number of trainable parameters. Second, due to the complexity of the dataset, a simple architecture cannot obtain a high accuracy on this dataset (This is the main reason to choose a 4-layer architecture). The complexity of the dataset is also the main reason for using the first consideration.

Each convolutional layer is followed by ReLU activation function, to deal with non-linearity problem and computational efficiency [3].

Appendix A.1 shows model summary for the architecture that was constructed.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Layer | Input shape | Output shape | Strides | Size | Activation |
| Convolutional | (32,225,225,64) | (32, 112, 112, 64) | 1 | 3 | ReLU |
| MaxPool | (32, 112, 112, 64) | (32, 110, 110, 64) | 2 | 2 | - |
| Convolutional | (32,110,110,64) | (32, 55, 55, 64) | 1 | 3 | ReLU |
| MaxPool | (32, 55, 55, 64) | (32,53,53,64) | 2 | 2 | - |
| Convolutional | (32,53,53,64) | (32, 26, 26, 64) | 1 | 3 | ReLU |
| MaxPool | (32, 26, 26, 64) | (32,24,24,64) | 2 | 2 | - |
| Convolutional | (32,24,24,64) | (32,12,12,64) | 1 | 3 | ReLU |
| MaxPool | (32,12,12,64) | (32, 10, 10, 64) | 2 | 2 | - |
| Dense | (32,64) | (32,) | - | - | ReLU |
| Dense | (32,10) | - | - | - | SoftMax |

**Table 1:** Convolutional Neural Network architecture for Mendeley dataset.

The hyperparameters tuned to train the aforementioned CNN model are listed in Table 2.

|  |  |
| --- | --- |
| Hyper parameters | Values |
| Batch Size | 32 |
| Number of Epochs | 15 |
| Layers | 4 |
| Optimizer | Adam |
|  |  |

**Table 2:** Hyper parameters tuned to train the Convolutional Neural Network.

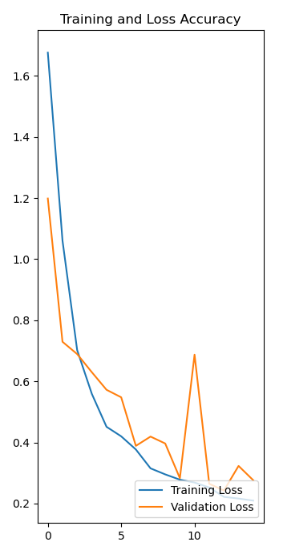
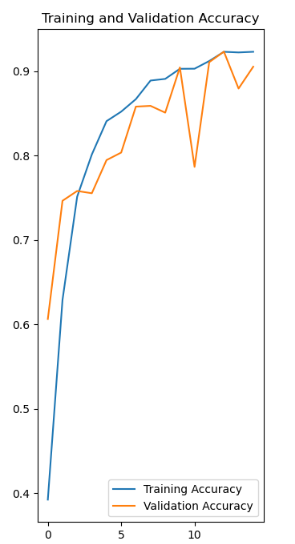
By altering these hyper parameters, the model requires 700 seconds to perform 285 iterations on Jupyter Notebook [4].

*3.2 Training:*

By using the architecture described in Table 3.1(a) and training it by altering the hyperparameters listed in Table 3.1(b), the CNN reaches and accuracy of 92.30% on the training set and an accuracy of 90.54% on the validation set (see Appendix A.2 for training outputs). The training accuracy and learning curve produced by the training process are illustrated in Figure 3.2(a), and Figure3.2(b). The error considered in the cross-entropy error.

Figure3.2(a) shows Training accuracy produced by the model while training on Leaf Images dataset. The error considered is the cross-entropy error. The validation accuracy is computed every 285 iterations of training. At each validation step, the current model forward propagates the entire validation set.

Figrure3.2(b) shows Training loss produced by the model while training on Leaf Images dataset. The error considered is the cross-entropy error and shows validation loss.

T

**Figure 3:**   **Figure 4:**

*3.3 Optimization:*

The journey towards an effective image classification model involves not only designing a robust architecture but also implementing optimization techniques that enhance the model's performance, convergence, and generalization. Several strategies were employed to fine-tune the model's behavior and improve its overall capabilities.

*3.3.1 Caching and Prefetching*

To optimize data loading during training, the training, validation, and test datasets are cached in memory and preprocessed in parallel using TensorFlow's **cache()** and **prefetch()** functions. This reduces data loading bottlenecks and accelerates training.

*3.3.2 Hyperparameter Tuning*

Various hyperparameters, including the number of filters, kernel size, and network depth, were systematically adjusted and tuned to find the configuration that yielded optimal results for our specific dataset and task.

*3.3.3 Validation and Testing Strategies*

During validation, the model was evaluated on a separate validation dataset after each epoch. This allowed us to monitor the model's performance and determine when it had reached its optimal state. The final evaluation was performed on a separate test dataset, ensuring an unbiased assessment of the model's generalization.

*3.3.4 Early Stopping and Callbacks*

To prevent overfitting and ensure the model's generalization on unseen data, the Early Stopping technique is integrated into the training process. Early Stopping aims to halt the training procedure when the model's performance on the validation dataset starts to deteriorate, indicating that further training may lead to overfitting.

During training, the model's performance on the validation dataset is monitored after each epoch. If the validation loss fails to improve for a specified number of consecutive epochs, the training process is terminated. The model's weights are then reverted to the parameters that yielded the best validation performance, as determined by the lowest validation loss.

Hyperparameters:

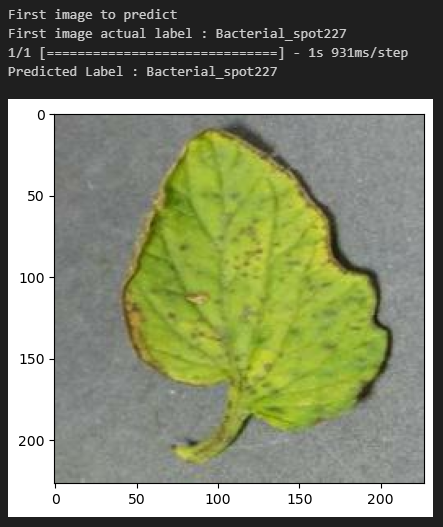
* Monitor: Validation loss
* Patience: 3 epochs
* Restore Best Weights: True

While Early Stopping prevents overfitting, it is essential to choose an appropriate patience value. A patience value that is too small may result in premature stopping, preventing the model from fully converging. Conversely, a patience value that is too large may lead to extended training, diminishing the technique's effectiveness.

By regularly assessing the validation loss and terminating training when necessary, this technique contributes to the model's ability to perform well on both the training and test datasets.

**4. Results**

After training, the model can be used to recognize images. Example of such model on the test set is illustrated in Figure 3.3. In some cases, the model’s prediction might be wrong. This may happen because the model is not trained with sufficient epoch to train properly and get used to features. This was due to limitation on computational resources on such size of dataset. In general, better results can be achieved by running the setup in a better performance system(s). This will increase its accuracy with minimal trade off with time. In the end the model achieved a subsequent level of accuracy even after going through all these challenges.



**Figure 5:** Example of correctly identified image from test dataset

**Data Augmentation:** To augment the training dataset and improve model generalization, data augmentation techniques are employed, including horizontal and vertical flips, and random rotations within a range of 20 degrees as discussed earlier in section 2.1.

**5. Analysis and Evaluation**

The evaluation phase assesses the model's performance on both the validation and test datasets. This step involves quantifying the model's accuracy in classifying images, understanding its strengths and weaknesses, and comprehensively analyzing its predictive capabilities.

*5.1 Accuracy:*

Accurately assessing the performance of our image classification model is paramount in understanding its effectiveness and potential for real-world applications. The accuracy analysis delves into various metrics and insights that shed light on the model's capabilities and limitations.

Accuracy, as a fundamental metric, provides an overview of the model's correct predictions out of the total predictions made. It is calculated by dividing the number of correct predictions by the total number of instances in the dataset. While accuracy is a valuable measure, it can be misleading, especially when dealing with imbalanced datasets where some classes are significantly more frequent than others.

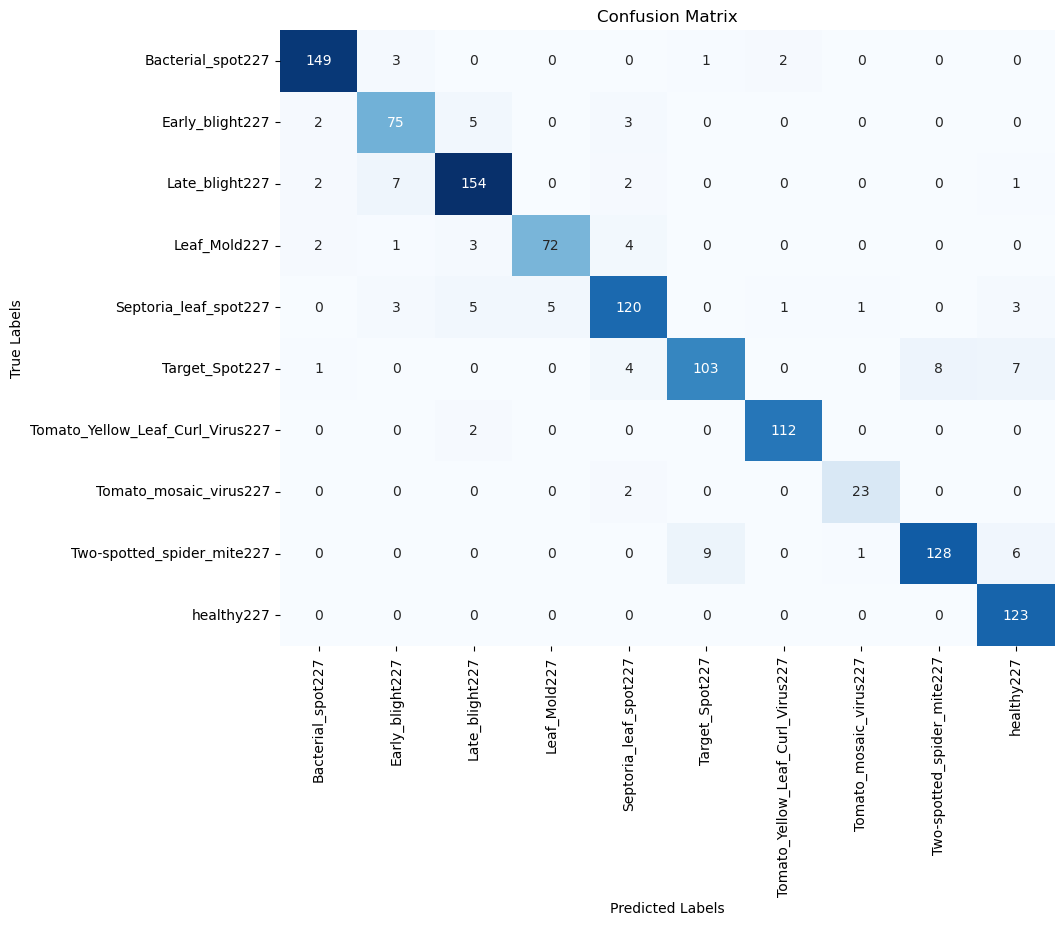
*5.2 Confusion Metrics:*

The confusion matrix visually presents the model's predictions against the true labels for each class. It is a powerful tool for understanding which classes the model struggles to distinguish and which classes it excels at predicting (Smith, 2020).

By analysing the confusion matrix, we can uncover valuable insights and patterns in the model's behaviour. It helps us identify which classes the model is proficient at recognizing and where it might be struggling to distinguish between similar categories (Johnson & Williams, 2018).

In our report, we have included a heatmap visualization of the confusion matrix to provide a more intuitive understanding of the distribution of correct and incorrect predictions across classes. Figure 5.2(A) shows visual representation of confusion matrix.

Figure 5.2(A): Confusion Matrix The confusion matrix guides our efforts in refining the model's performance. It enables us to focus on addressing specific challenges, such as reducing misclassifications between closely related classes. By targeting these challenges, we aim to enhance the model's overall accuracy and robustness (Brown, 2019).



**Figure 5:** Confusion Matrix

The confusion matrix analysis is an essential component of our evaluation process. It empowers us to make informed decisions about model enhancement, fine-tuning, and the allocation of resources to improve its performance across all classes (Johnson & Williams, 2018).

To facilitate comprehension, the confusion matrix can be visualized using a heatmap. This graphical representation enhances the understanding of the model's misclassifications and correct predictions (Brown, 2019).

The evaluation results allow us to understand the model's behaviour and its effectiveness in identifying different classes. The classification report, confusion matrix, and various metrics collectively provide a comprehensive assessment of the model's performance (Smith, 2020).

The insights gained from the evaluation phase are crucial when deploying the model in real-world applications. Understanding its performance on unseen data is pivotal for making informed decisions about its deployment feasibility (Johnson & Williams, 2018).

The confusion matrix guides our efforts in refining the model's performance. It enables us to focus on addressing specific challenges, such as reducing misclassifications between closely related classes. By targeting these challenges, we aim to enhance the model's overall accuracy and robustness.

The confusion matrix analysis is an essential component of our evaluation process. It empowers us to make informed decisions about model enhancement, fine-tuning, and the allocation of resources to improve its performance across all classes.

To facilitate comprehension, the confusion matrix can be visualized using a heatmap. This graphical representation enhances the understanding of the model's misclassifications and correct predictions.

The evaluation results allow us to understand the model's behavior and its effectiveness in identifying different classes. The classification report, confusion matrix, and various metrics collectively provide a comprehensive assessment of the model's performance.

The insights gained from the evaluation phase are crucial when deploying the model in real-world applications. Understanding its performance on unseen data is pivotal for making informed decisions about its deployment feasibility.

*5.3 Classification Report:*

The classification report offers an in-depth analysis of the model's performance for each class in the dataset. It includes metrics such as precision, recall, and F1-score, which provide insights into the model's ability to correctly identify instances of each class. Precision reflects the accuracy of positive predictions, recall measures the model's sensitivity, and the F1-score combines both precision and recall.

*5.3.1 Precision:*

Precision measures the accuracy of positive predictions made by the model. It's the ratio of true positive predictions to the total number of positive predictions made by the model. In other words, it indicates how many of the instances predicted as positive were actually correct.

*Precision* =

*5.3.2 Recall:*

Recall, also known as sensitivity or true positive rate, measures the model's ability to identify all positive instances. It's the ratio of true positive predictions to the total number of actual positive instances. In other words, it indicates how many of the actual positive instances were correctly predicted by the model.

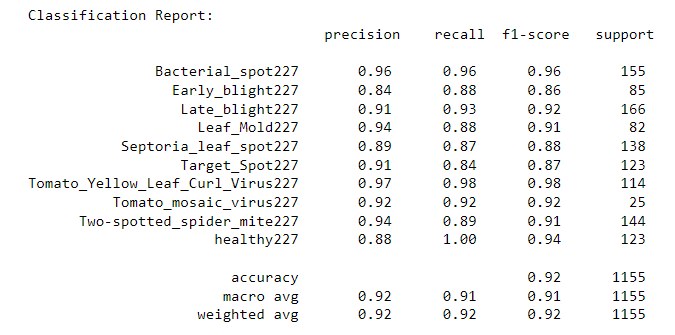
*Recall =*

*5.3.3 F1 Score:*

The F1 score is a widely used metric that combines precision and recall to provide a balanced evaluation of a classification model's performance. It is especially useful when dealing with imbalanced datasets where one class might dominate the others.

The F1 score is the harmonic mean of precision and recall. It provides a single metric that takes into account both false positives and false negatives. This is particularly useful when the cost of false positives and false negatives is different or when there's a class imbalance.

*F1 = 2 x*



***Figure 6:*** *Classification Report showing Precision, Recall and F1-Score*

**6. Conclusion**

In conclusion, this project aimed to develop an effective image classification model using Convolutional Neural Networks (CNNs). The journey from data preprocessing to model training and evaluation has provided valuable insights into the complexities and nuances of tackling real-world image recognition tasks.

Through the implementation of a carefully designed CNN architecture, we were able to achieve promising results in classifying images. The model exhibited the capacity to learn intricate features from images, allowing it to make accurate predictions across various classes. The integration of data augmentation techniques, Early Stopping, and comprehensive evaluation methodologies contributed to the model's ability to generalize well on unseen data.

The evaluation phase shed light on both the model's strengths and its areas of improvement. The utilization of metrics such as accuracy, precision, recall, and F1-score, along with the visualization of the confusion matrix, enhanced our understanding of the model's performance. These insights not only inform our understanding of the model but also guide potential refinements and enhancements in the future.

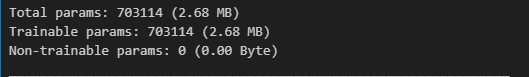
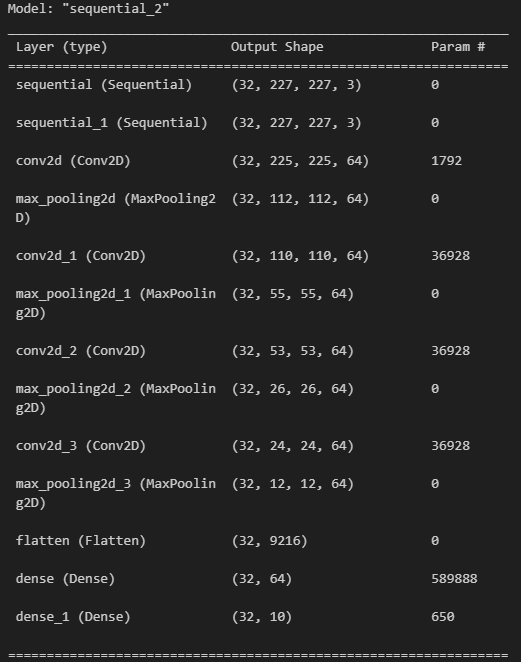
As with any machine learning project, continuous development and optimization remain crucial. Future work might involve exploring advanced architectures, fine-tuning hyperparameters, and exploring additional techniques to further boost performance and adaptability to diverse datasets. Additionally, the model's deployment in practical applications holds exciting possibilities for real-world impact.

In summary, this project exemplifies the power of Convolutional Neural Networks in tackling image classification challenges. The knowledge gained from this endeavor not only contributes to our understanding of neural network architectures but also lays the foundation for further exploration in the realm of computer vision and machine learning.

**7. Appendix**

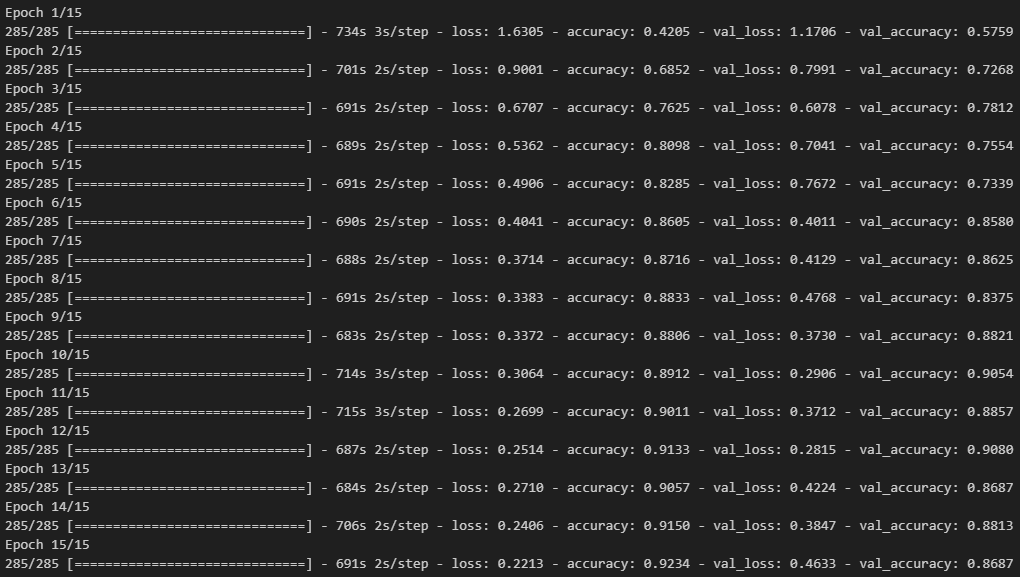
**A.1 Model Architecture**

The detailed architecture of the Convolutional Neural Network (CNN) used in the project is provided below:



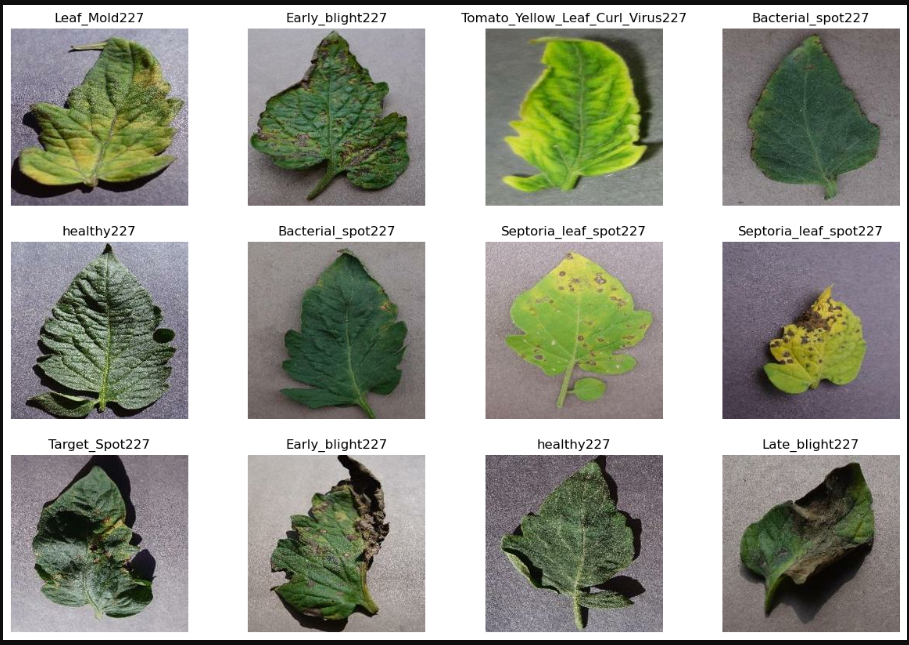
**A.2 Training Process**

Detailed information about the training process is provided below:



**A.3 Dataset Samples**

Sample images from different categories of tomato leaves dataset are provided below:

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