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Chili Leaf Health Classification using Xception Pretrained Model

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Abstract

As one of the high-demand horticultural crops, chili peppers have a significant impact on the economy of Indonesia. However, despite the growing demand and interest in chili peppers, their production often faces disruptions due to crop failures. One of the leading causes of such failures is pests and diseases. Among all parts of the chili plant, chili leaves are the most susceptible to damage. Distinguishing between healthy and unhealthy chili leaves can serve as an early detection step for chili diseases and preventive measures to contain their spread. Convolutional Neural Network (CNN) are effective algorithms for image classification. The development of CNN has led to the use of models previously trained on large datasets to accurately classify relatively small datasets. One such pretrained model known for its exceptional classification capabilities is Xception. By utilizing the pretrained Xception model trained on the ImageNet dataset for the classification of healthy and unhealthy chili leaf images, our model achieved an accuracy of 91% on a dataset containing 2136 images. Furthermore, the model achieved a 100% success rate by correctly predicting all 10 out of 10 given images.

Keywords: Chili, Classification, CNN, Pretrained Model, Xception.

1 Introduction

Chili (*Capsicum spp.*) is a horticultural plant extensively cultivated due to its substantial economic value. In Indonesia, the Central Statistics Agency (BPS) reported a consumption of 636.56 tons of large chili variants by households in the year 2022. This represents a 6.78% increase, equivalent to 40.42 thousand tons, compared to the consumption in 2021 [1]. However, despite the surging demand, chili production frequently encounters disruptions, including crop failures resulting from pest infestations and diseases.

Chili diseases can stem from various factors such as bacteria, fungi, viruses, or nematodes [2]-[3], with chili leaves being particularly susceptible [3]. Consequently, early detection of chili diseases is imperative to ensure sustained chili production.

The evolution of information technology has streamlined plant disease detection. Machine learning techniques stand as a promising solution for precise and efficient plant disease detection. Among the widely adopted algorithms, the Convolutional Neural Network (CNN) is notable for its architecture, encompassing layers that effectively detect features hierarchically [4]. Nonetheless, the availability of diverse and high-quality data remains a common challenge in utilizing deep learning for plant disease detection. Leveraging pretrained models on extensive datasets can be instrumental in addressing data limitations [5]–[7].

Given the commendable performance of CNN, this study aims to classify chili leaf health using one of the pretrained models based on the CNN architecture, specifically Xception. The dataset comprises a total of 2136 images, encompassing 1068 images of healthy chili leaves and 1068 images of unhealthy chili leaves. This research is anticipated to enrich the body of knowledge concerning early disease detection in chili, thereby supporting the sustainable chili farming sector in Indonesia.

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2 Literature Review

In this study, a literature review of previous research serves as the foundation for the investigation. CNN-based models have been widely used to detect diseases in various plants, such as tomato [8], [9], apple [10], [11], grape [11], [12], and many more [13]–[16]. In detecting chili disease, the use of Convolutional Neural Networks (CNN) has also been done by previous researchers. One such study being conducted by Rosalina and Wijaya [17]. They developed a desktop application-based system capable of capturing images of chili leaves using a Raspberry Pi camera, performing image processing on these images, and subsequently determining whether the leaves were healthy or diseased, along with providing probability values. The chili leaf dataset used in this research was constructed by the researchers themselves and comprised a total of 1000 images, evenly split between 500 healthy chili leaf images and 500 diseased chili leaf images. The model utilized in this study was a CNN-based model with the architecture depicted in Figure 1. The system achieved its primary function successfully, which was to recognize chili leaves and detect whether they were infected with diseases, achieving 100% accuracy in the 'Adequate lighting and distance <1 meter' testing scenario.

Another study, conducted by Dzaky [18], focused on recognizing several chili leaf diseases, including curling, wilting, and yellowing virus, using a CNN model with the AlexNet architecture. The dataset in this research comprised 461 images and underwent preprocessing, including square cropping, data segmentation using GrabCut, data resizing, and data augmentation. The best model achieved 90% accuracy, an 88% F1 score, a loss of 0.0213 after 40 epochs, and a learning rate of 0.01.

Subsequently, Saputra et al. [19] conducted research utilizing a CNN and the pretrained DenseNet201 model for the recognition of various chili leaf diseases, such as healthy, leaf curl, leaf spot, whitefly, and yellowing. In this study, the CNN model obtained 94% accuracy with a 100% success rate, correctly predicting 15 out of 15 images. Meanwhile, the DenseNet201 model achieved 92% accuracy with a success rate of 87%, accurately predicting 13 out of 15 images.

Kanaparthi et al. [20] conducted a similar study using the SqueezeNet-CNN model on a dataset containing 160 images. The study conducted experiments using different optimizers, namely SGDM, Adam, and RMSprop. With an epoch range of 20-40, the model with the RMSprop optimizer showed the best results, achieving 100% accuracy at 35 epochs.

Drawing from the previous research [18]-[20], this study shares similarities in terms of using relatively small datasets. However, the CNN model proposed in this study differs from the CNN models used in the mentioned studies. In this research, the CNN model to be employed is Xception, which has been pretrained on the ImageNet dataset. Xception is a Convolutional Neural Network architecture based on the Inception architecture, designed to strike a balance between computational efficiency and neural network performance. The initial layers of the network employ various parallel convolution sizes to capture features at different scales efficiently, enabling the network to learn complex features effectively.

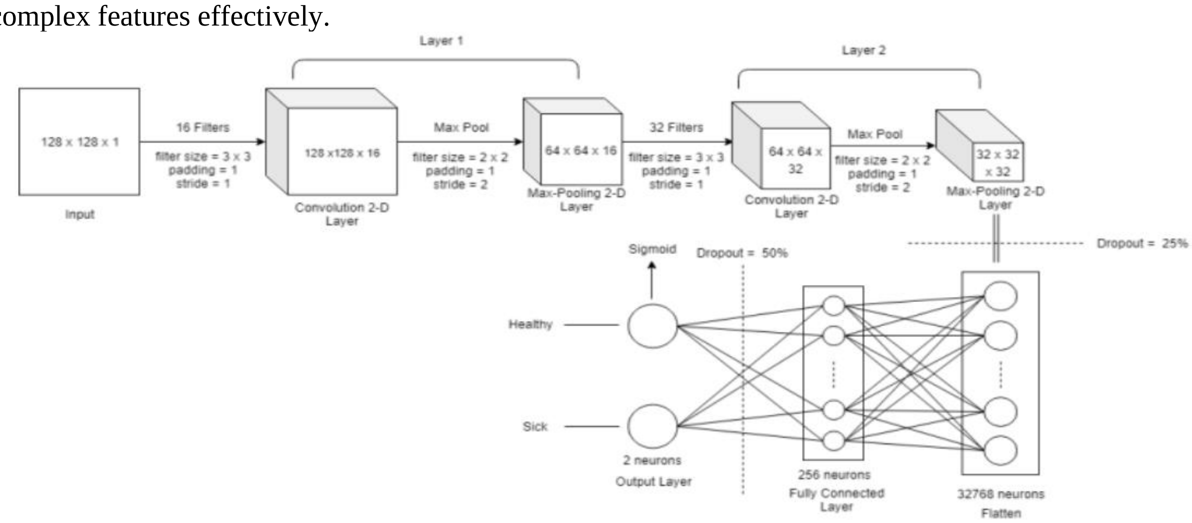

Figure 1. CNN Architecture in Rosalina [5]

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3 Method

In this research, several stages were undertaken to classify healthy and unhealthy chili leaf images using Xception, as illustrated in Figure 2.

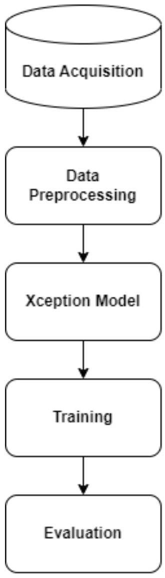

Figure 2. Research Stages

An explanation of the research stages is as follows:

1. Data Acquisition

   During the data acquisition stage, healthy and diseased chili leaf images were collected from various sources on the internet, including Canva Images and Roboflow Universe [21]. A total of 2136 chili leaf images were collected, with 1068 being healthy chili leaf images and 1068 being diseased chili leaf images. Figure 3 displays some sample images from the gathered dataset.

Figure 3. Sample Images of The Dataset

2. Data Preprocessing

   After data collection, preprocessing of the data was carried out before it could be used for training. This stage involved several processes, including resizing, dividing the data into

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training and test sets, data augmentation, and data normalization. Image resizing was performed, converting images to a size of 225 × 225 pixels [22], [23]. Images with non-1:1 aspect ratios were first cropped to a square aspect ratio before being converted to 225 × 225 pixels. All processes in this stage were conducted using Adobe Photoshop CC 2019, and the resizing process was automated using Photoshop CC 2019's Batch Resize Images tool.

After resizing, the data was divided into two separate folders: training and test sets. In this research, 75% of the data, or 800 images, were allocated for training, while 25% of the data, or 268 images, were designated for testing. Each set comprised two classes: healthy and unhealthy.

To introduce variability into the dataset, the next preprocessing step involved data augmentation. Data augmentation was performed on-the-fly using Keras ImageDataGenerator.

The final preprocessing step was data normalization, which was done to prevent large pixel values from dominating the learning process. This step was also conducted using the Keras library's ImageDataGenerator class.

3. Xception Model

Xception is a convolutional neural network (CNN) architecture based on the Inception architecture, designed to balance computational efficiency and neural network performance. The initial layers use various convolution sizes in parallel to capture features at different scales, allowing the network to efficiently learn complex features. The Xception architecture (Figure 4) is similar to Inception but replaces the standard convolutional layers in the Inception module with depthwise separable convolutions [24]. This modification results in a more computationally efficient and powerful network architecture. Xception was primarily designed for image classification tasks, but its principles and ideas have influenced the design of subsequent neural network architectures. On the ImageNet dataset, Xception achieved an accuracy of 94.5%, surpassing InceptionV3, which achieved 94.1% [24].

In this study, the fully connected layer present at the top of the Xception network will not be utilized. Instead, several new layers will be added. To transform the output into a one-dimensional format, a Flatten Layer will be employed. Subsequently, a Dropout Layer with a rate of 0.5 will be added to mitigate overfitting. Following that, there will be three hidden layers with 512, 256, and 128 neurons, all utilizing the ReLU activation function. Finally, the output layer will consist of a single neuron for binary classification, utilizing the sigmoid activation function.

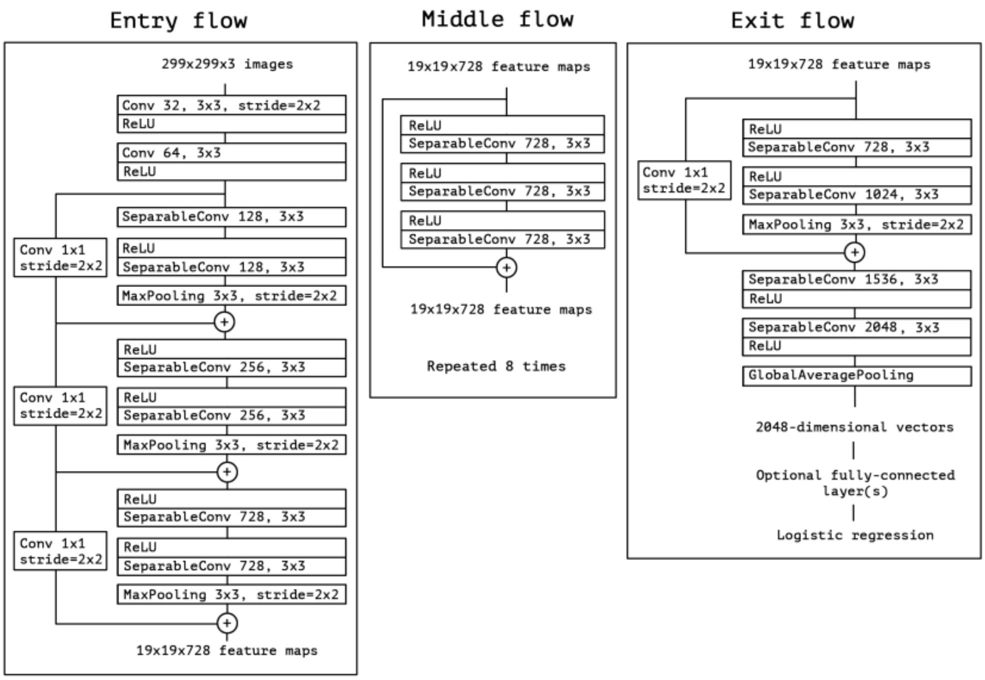

Figure 4. The Xception Architecture [9]

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4. Training

   The training process was conducted with 20 epochs and a batch size of 64. The optimizer used in this research was Adam with the default learning rate. Since the task was binary classification, the loss function employed was Binary Cross Entropy. The metric used to monitor the model's performance during training was Accuracy.

5. Evaluation

   Following training, the next step was model evaluation. Evaluation involved testing the trained model using the test dataset.

4 Results and Analysis

In this section, we will discuss the performance evaluation results and analysis of the Xception model.

4.1 Training Result

The training results are visualized through Accuracy and Loss graphs as shown in Figures 5 and 6. From Figures 5 and 6, it can be observed that the model exhibits reasonably good performance, although the training accuracy values appear somewhat fluctuating. This is indicated by the close similarity between the training accuracy and loss values compared to the validation accuracy and loss. The final accuracy value at epoch 20 is 91%, with the highest accuracy achieved at epoch 15, reaching 92%. The accuracy graph is depicted in Figure 5. Figure 6 illustrates the loss values of the model. The final loss value at epoch 20 is 0.2003, representing the lowest loss value throughout the training process.

Figure 5. Training Accuracy Graph

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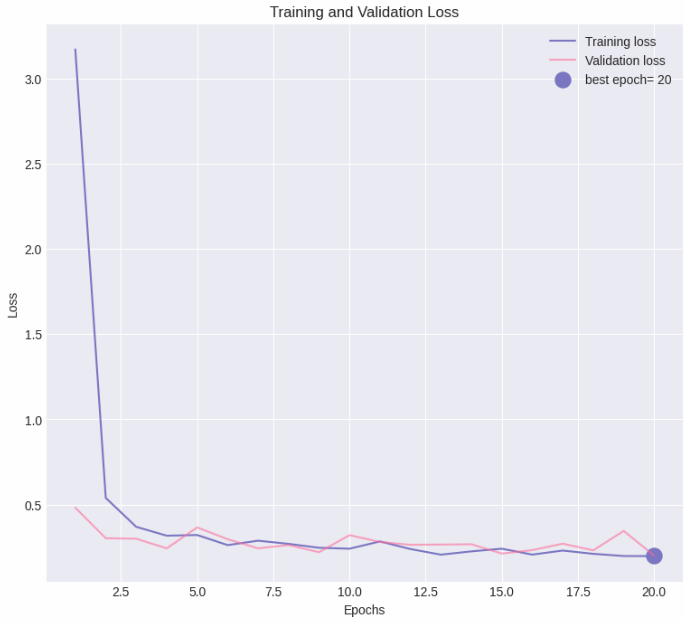

Figure 6. Training Loss Graph

4.2 Confusion Matrix and Classification Report

The confusion matrix results are presented in Figure 7. From Figure 7, it can be observed that out of 268 healthy leaf images, 248 were correctly predicted, while 20 were misclassified. For unhealthy leaf images, out of 268, 241 were correctly predicted, and 27 were misclassified.

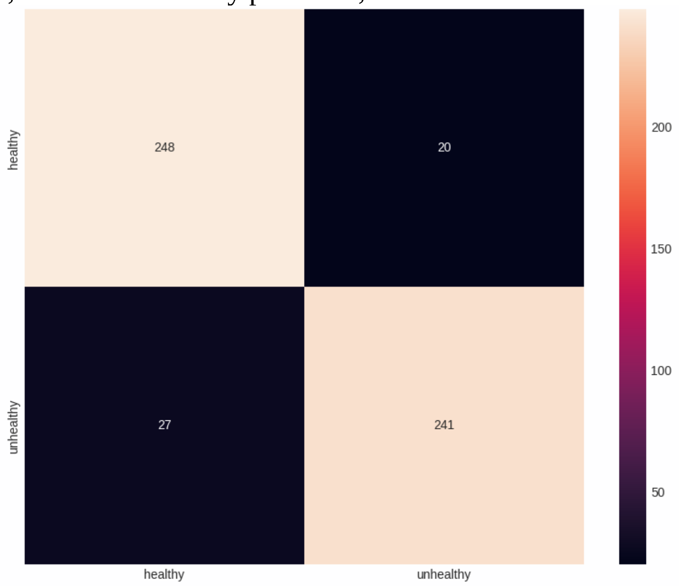

Figure 7. Confusion Matrix

The classification report for the model is displayed in Figure 8. From the report, it is evident that the pretrained Xception model achieved an accuracy rate of 91%.

	precision	recall	f1-score	support
healthy	0.90	0.93	0.91	268
unhealthy	0.92	0.90	0.91	268
accuracy			0.91	536
macro avg	0.91	0.91	0.91	536
weighted avg	0.91	0.91	0.91	536

Figure 8. Classification Report

4.3 Example of The Test Result and Feature Map

An experiment involving 10 random images was conducted. the results can be seen in Figure 9. From 10 images tested, 10 out of 10 images are correctly predicted. It can be concluded that the model achieved a 100% success rate in predicting the given images.

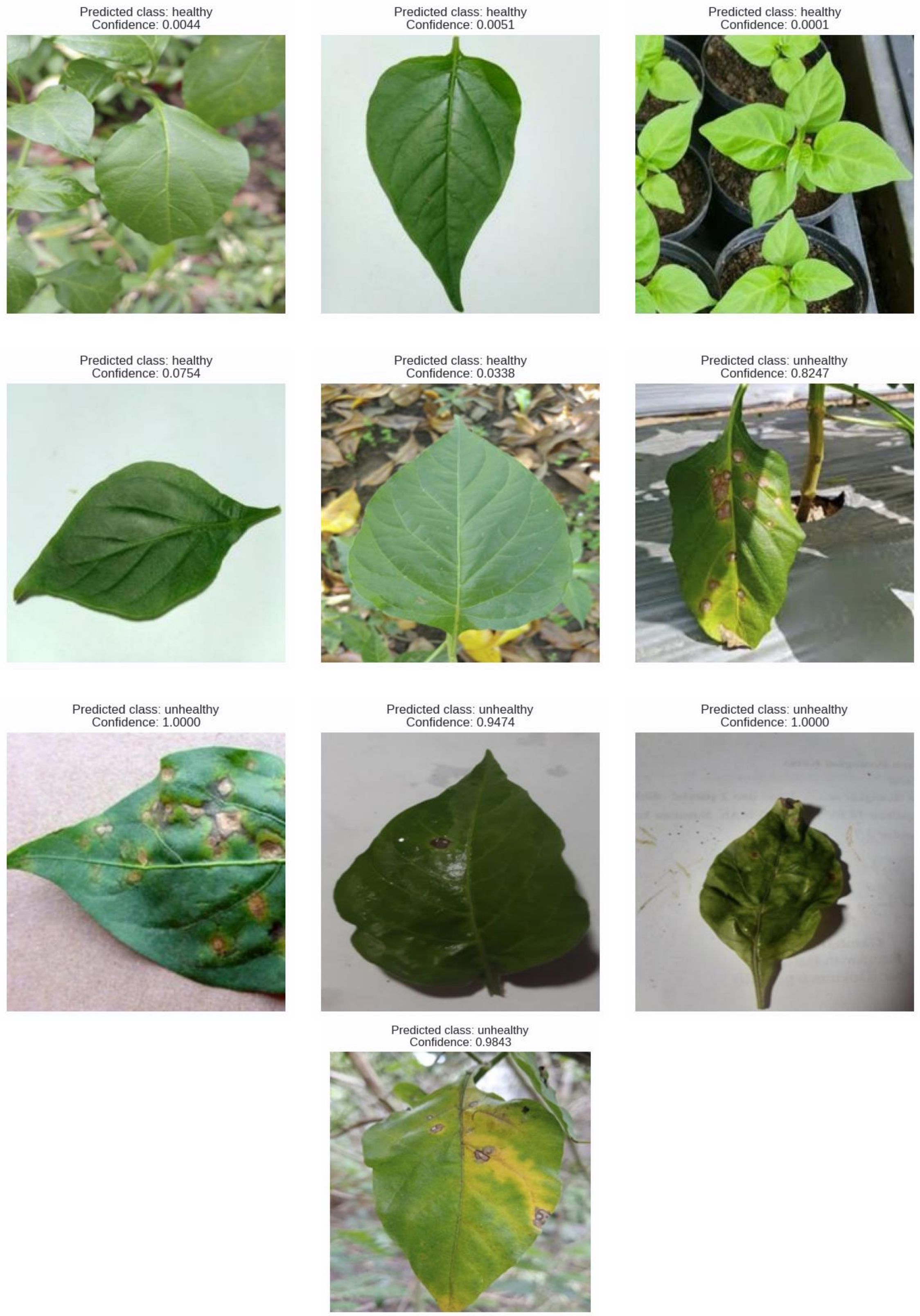

Figure 9. Example of The Test Result

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Feature maps represent the outcomes of filters applied by the convolutional layer. Figure 10 provides an example of feature maps extracted by the model.

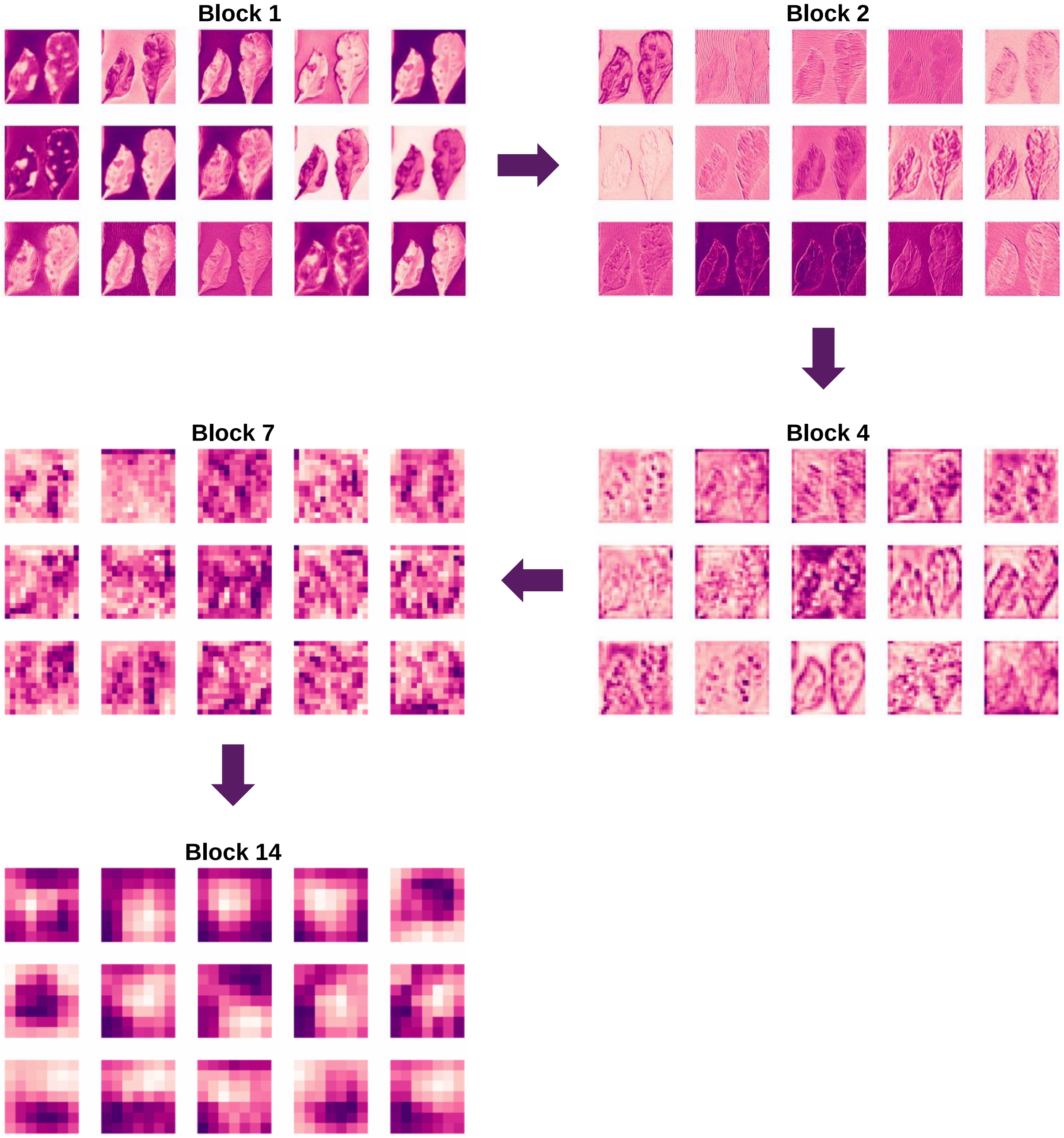

Figure 10. Feature Map Examples of The Trained Model

5 Conclusion

This study successfully conducted the classification of healthy and unhealthy chili leaf images using a pretrained Convolutional Neural Network (CNN) model, Xception. The research was carried out with a dataset consisting of 2136 chili leaf images, comprising 1068 healthy chili leaf images and 1068 unhealthy chili leaf images. The research outcomes indicate that the Xception model which previously trained on the ImageNet dataset can effectively predict healthy and unhealthy chili leaf images to a significant degree. The model achieved an accuracy rate of 91%. Furthermore, the model exhibited a success rate of 100% by accurately predicting all 10 out of 10 given images.

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