A Multi-Scale Feature Fusion Network for Detecting and Classifying Apple Leaf Diseases

Assad S. Doutoum[1][a], Recep Eryigit[2][b] and Bulent Tugrul[3][c]

[1]*Computer Science Department, University of Ndjamena, Farcha, Ndjamena, Chad*

[2]*Ankara University, Department of Computer Engineering, Ankara, Turkey*

[3]*Ankara University, Department of Computer Science, Ankara, Turkey*

Keywords: Deep Learning, Multi-Scale CNN, Apple Leaf Diseases.

Abstract: Early detection and identification of leaf diseases reduce expenses and increase profits. Thus, it is essential for producers to be aware of the symptoms and indications of these leaf diseases and take the necessary preventative measures. Early diagnosis and treatment can also help prevent the disease from spreading to healthy plants. For successful disease control, regular inspections of orchards are essential. As well as being costly and time-consuming, traditional methods require a great deal of labor. However, the use of modern technologies and methods such as computer vision will both increase successes and reduce costs. Deep learning methods can be used to detect and classify diseases, as well as predict the likelihood of them occurring. Though, a particular CNN architecture may focus on a subset of features, while another may discover other additional features not extracted from the dataset. Robust classification models should be developed that perform consistently well when different environmental factors such as light, angle, background and noise vary. To solve these challenges, this study proposes a multi-scale feature fusion network (MFFN) that combines features from different scales or levels of detail in an image to improve the performance and robustness of classification models. The proposed method is evaluated on a publicly available dataset and is shown to improve the performance of the original models. Four branches applied to CNN architectures were simultaneously trained and merged to accurately classify and predict infected apple leaves. The merged model was able to detect infected leaves with a high degree of accuracy, significantly through the combined models. The merged model was able to accurately predict the unhealthy apple leaves with a 99.36% on the training accuracy, 98.90% on the validation accuracy, and 98.28% on the test accuracy. The results show that combining the models is an effective way to increase the accuracy of predictions under volatile conditions.

1 INTRODUCTION

Plant leaf diseases severely affect the quality and productivity of agricultural products. The agricultural industry loses millions of dollars every year due to yield loss and unnecessary or misuse of pesticides (Alsayed et al., 2021). It is therefore crucial to detect and diagnose plant diseases early to prevent their spread and minimize their impacts. Several pathogens such as Black Rot disease, Cedar Rust disease, and Scab disease may affect apple leaves (Su et al., 2022; Nandhini and Ashokkumar, 2022). Traditional methods of detecting plant diseases require specialized knowledge and expertise in plant pathology. These methods are often time-consuming and require the use of expensive equipment, making them inaccessible to those without adequate budgets. These limitations hinder the ability to detect and monitor diseases on small farms and in low-income countries where resources and experts are scarce. Consequently, advanced technologies and automated systems are required to detect plant sicknesses at an early stage. With the help of such technologies it is possible to detect, classify and diagnose plant diseases more quickly and accurately. Thanks to these methods, agricultural enterprises can save time and money and gain a competitive advantages over their competitors on both national and international markets.

Various machine learning and deep learning methods have been used to detect and classify plant ill-

[a] https://orcid.org/0000-0003-4822-1876
[b] https://orcid.org/0000-0002-4282-6340
[c] https://orcid.org/0000-0003-4719-4298

Doutoum, A. S., Eryigit, R., Tugrul and B.
A Multi-Scale Feature Fusion Network for Detecting and Classifying Apple Leaf Diseases.
DOI: 10.5220/0013447700003967
In *Proceedings of the 14th International Conference on Data Science, Technology and Applications (DATA 2025)*, pages 13-20
ISBN: 978-989-758-758-0; ISSN: 2184-285X

nesses (Barbedo, 2018; Doutoum and Tugrul, 2023). It is suggested that deep learning methods shorten the time-consuming and cost-efficient process of feature extraction in image processing (Yan et al., 2020). The models obtained through deep learning methods demonstrate significantly improved accuracy and robustness compared to traditional machine learning methods. In traditional machine learning, prediction or classification models are trained using manually extracted features. In contrast, deep learning models have the ability to automatically extract features from images and build the model on them. As a result, manual feature extraction is no longer necessary, increasing the efficiency and reducing the cost of classification methods. Furthermore, deep-learning algorithms have the potential to recognize complex correlations and patterns as well as various high-level elements that are invisible to humans. As a result, they are more suitable for tasks that require more domain-specific knowledge and experience.

Feature fusion uses multiple scales or levels of detail in computer vision and image processing to integrate facts into feature representation to enable a better understanding of visual elements (Elizar et al., 2022). As a result, they are more resistant to changes in object size, orientation, and scale, because characteristics at various sizes can give complementing information. This may rise item recognition and classification accuracy, as well as the capability to distinguish things in a more problematic context. There are many ways of accomplishing multi-scale feature fusion in computer vision. One possible approach is to use distinct Convolutional Neural Network (CNN) architectures to extract features of varying sizes and aspects and then efficiently integrate them. Integrating detailed features from small scales with contextual knowledge from large scales yields more comprehensive and robust models.

The contributions of this article can be summarized as follows: By proposing an architecture based on multi-scale CNN for apple leaf disease classification and prediction, we improve the overall performance of the model by allowing it to better understand the spatial structure of the images, leading to more accurate predictions. Our proposed model is based on parallel training of big datasets, is less complex, and has accurate results compared with other deep learning models (Yan et al., 2020; Gündüz and Yılmaz Gündüz, 2022). According to the comparison dataset, our model achieved the highest accuracy result of 98.28% on the test set.

2 METHODS AND MATERIALS

The following section provides detailed information about the Apple data source. Additionally, the pre-processing procedures applied to the dataset and the training process of the proposed multi-scale feature fusion network (MFFN) will be explained.

2.1 Dataset

The dataset utilized in this study consists of images with healthy and unhealthy apple leaves. As can be seen from Table 1, there are four main classes within the dataset. The first class contains leaf images of Black Rot disease. The second class contains images of Cedar Rust disease. The third and fourth classes contain images of healthy leaves and Scab disease respectively. In total, there are 10,173 images of apple leaves in the dataset (Hughes and Salathé, 2015). The class distribution of the apple dataset is shown in Table 1.

2.2 Data Pre-Processing

Image pre-processing and validation is an essential step to calibrate the images before being trained by the deep learning model (Divakar et al., 2021). Deep learning classifiers require huge datasets to overcome over-fitting problems and obtain better precision level of achievement. It is therefore necessary to perform an augmentation techniques in order to expand the dataset from the one that currently exists. This requires changes such as resizing, zooming, rotating, or adjusting the color of the images. Nevertheless, it is necessary to split the dataset into training, validation, and testing sets (Gündüz and Yılmaz Gündüz, 2022). Using the image data augmentation techniques, we horizontally shift the dataset's images.

2.3 Dataset Augmentation Techniques

Common data augmentation techniques include flipping, rotating, and scaling images to create new variations. Other methods involve adjusting brightness, contrast, and adding noise to enhance the dataset further. By expanding the dataset, it allows models to learn features more robustly and generalize better to unseen data. Additionally, it introduces variability that can make the model more resilient to noise and variations in real-world data. This leads to improved accuracy and performance across diverse scenarios. Common data augmentation techniques include flipping, rotating, and scaling images to create new variations. Other methods involve adjusting brightness,

Table 1: Distribution of the apple dataset.

Disease type	Black Rot	Cedar Rust	Healthy leaf	Scab	Total
Number of images	2352	2792	2510	2519	10173

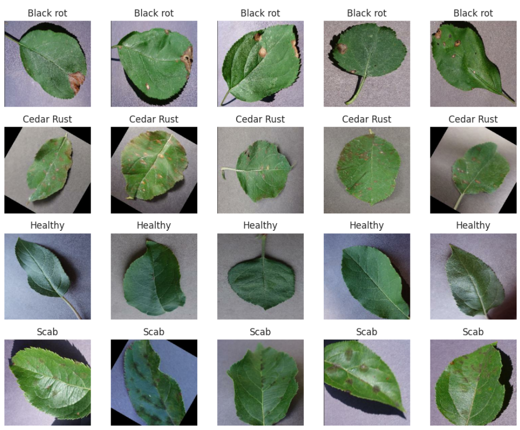


Figure 1: Sample of images after the augmentation processes.

contrast, and adding noise to enhance the dataset further (Baranwal et al., 2019; Su et al., 2022). Table 2 displays the augmentation details. Figure 1 shows a sample of images after the augmentation processes.

Table 2: Augmentation parameters.

Parameter	Value
Rotation	40
Width	0.2
Height	0.2
Horizontal flipping	True
Vertical flipping	True
Shear	0.2
Zoom	0.2

2.4 Data Splitting

The dataset used in this study contains a total of 10173 images. The dataset is divided into three folders: the training and the validation sets contain 6353 and 2014 images respectively. The remaining 1806 images are assigned to the test set. The validation set is allocated to assess the model's generalization ability. If over-fitting is observed, hyper-parameters such as learning rate, epoch size, or number of layers can be fine-tuned to enhance the model's performance. This process of fine-tuning hyper-parameters based on validation results help to identify the optimal configuration that maximizes the model's performance on unseen test data. The apple dataset is divided into four classes, and each class contains one apple disease (Yadav et al., 2022).

2.5 Multi-Scale CNN Model Structure

The improved model architecture is based on the multi-scale CNN model, which is shown in Figure 2. Our network consists of one input image shape with a size of 224×224×3 divided into four branches. Each CNN branch has one convolution layer (64×64) followed by Batch Normalization layers (BN) and Max-Pooling layers. After each Batch Normalization we use ReLu as an activation function. We add separable layers before concatenating the four branches networks. Following the merging of the CNN networks, two dense layers are added to the network. Table 3 displays the description of the Multi-scale CNN network architecture.

Table 3: Description of MFNN architecture.

Layer	CNN (Input=224 × 224 × 3)
Conv1	1 × 1
	64 × 64
MaxPool	2 × 2
Conv2	1 × 1
	64 × 64
MaxPool	2 × 2
Conv3	1 × 1
	64 × 64
MaxPool	2 × 2
Conv4	1 × 1
	64 × 64
MaxPool	2 × 2
Concatenate	conv1, conv2 , conv3 , conv4
Conv5	3 × 3
	64 × 64
MaxPool	2 × 2
Conv6	3 × 3
	64 × 64
MaxPool	2 × 2
Conv7	3 × 3
	128 × 128
MaxPool	2 × 2
Dense	-

2.6 Experimental Environment and Parameters

For the purpose of training, our proposed model for classification and detection of Apple leaf diseases, used TensorFlow/Keras framework, and Python 3.11

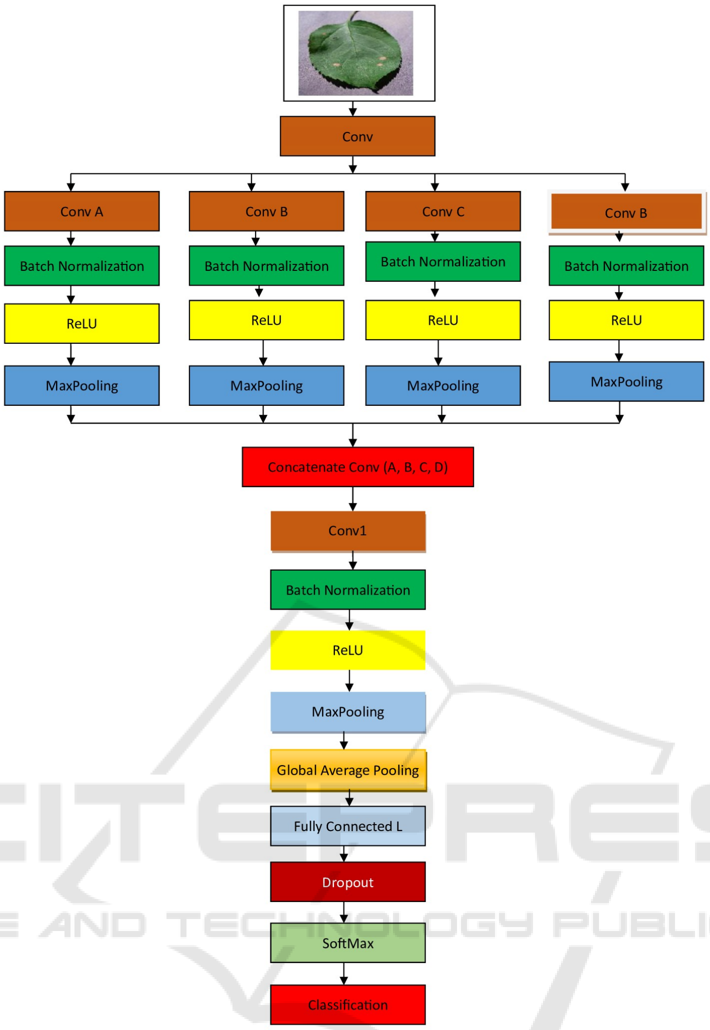


Figure 2: MFFN architecture.

version. Table 4 shows the hardware and software details of the experimental environment. The Apple dataset was divided into three parts: training, validation, and testing sets. There are multiple parameters applied to the training and validation dataset. Table 5 shown the parameters utilized during training and validation.

3 EXPERIMENTAL RESULTS AND ANALYSIS

This section evaluates the performance of our proposed MFFN model in the classification and detection of apple leaf diseases. The experimental evaluates and analyzes confusion metrics and compares the module with other existing models. To evaluate the efficiency of the proposed model we trained on the apple leaf dataset, which consists of four distinct classes. The percentage of true guesses in prediction results compared to all guesses is known as accuracy rate. Recall rate is the percentage that a category is accurately predicted in all actual values, whereas precision rate is the percentage that a category is correctly forecasted in all prediction outcomes.

3.1 Evaluation Metrics

The confusion matrix is used to evaluate the achievements of our model. A confusion matrix is presented in this section for a thorough analysis. The confusion matrix's rows correspond to the actual category labels, while its columns correspond to the labels that the model predicted. Through the number of cases of True Positive (TP), False Positive (FP), True Negative

Table 4: Experimental hardware and software.

Name	Model
Framework	TensorFlow/Keras
GPU	NVIDIA RTX A4000
CPU	Intel(R) Xeon(R) W-2235 CPU @ 3.80GHz, 3792 MHz
OS	Win 11 Pro
Ram	32 GB
Python	3.11

Table 5: Experimental parameters setting.

Parameter Name	Parameter setting
Learning rate	0.001
Batch size	32
Optimizer	Adam
Activation function	SoftMax
Beta1	0.9
Beta2	0.999
Amsgrad	False
Iteration epochs	100

(TN), and False Negative (FN), the confusion matrix produces four assessment metrics: accuracy, recall, specificity, and F1 score. The formula for each metric is given below.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

It is evident from the confusion matrix displayed in Figure 3 that the majority of classification errors occur in scenarios where there is a distinction between cedar rust and scab. One of the main reasons for this is that the complex background context of the data set facilitates errors in judgment. The early disease spots in the Scab and Cedar rust dataset are primarily small-scale features with intricate background settings. Another reason for that is the texture of the affected areas might appear irregular or spotted, which is a common feature between the two diseases. Additionally, the impact of nearby leaves that fall into different health categories results in classification errors and insufficient reliable information about the final marks that the model obtains. Nonetheless, the model's overall effect still complies with the requirements of the leaf disease detection scenario. Figure 4 displays precision, recall, and F1 scores for each class.

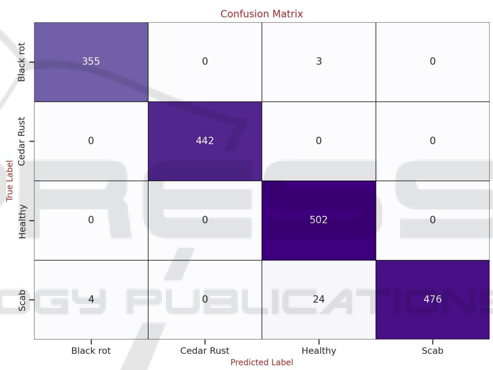


Figure 3: Confusion matrix of the MFFN.

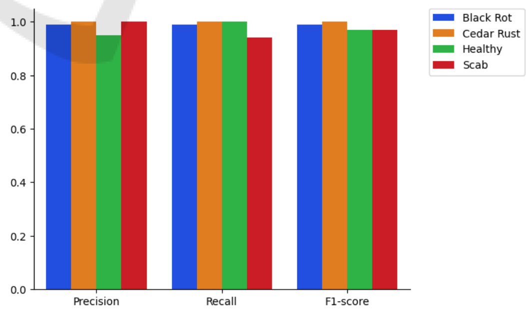


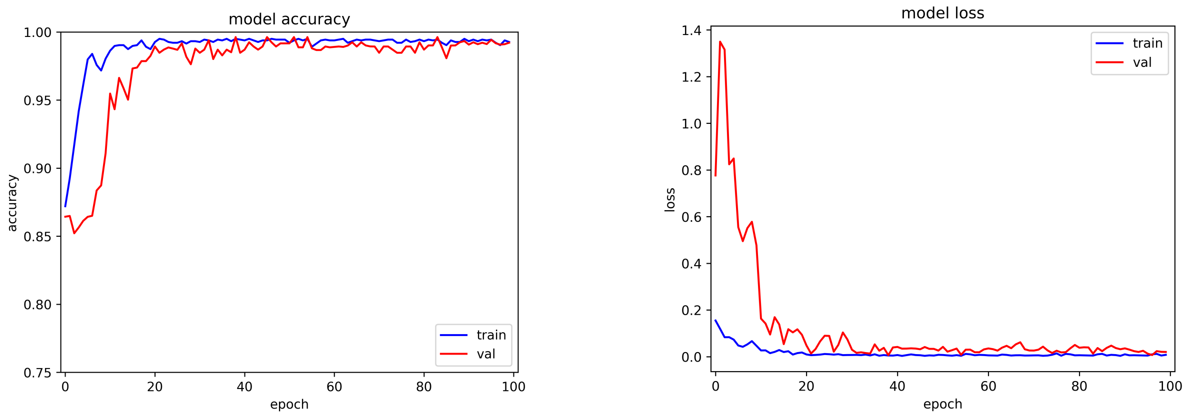
Figure 4: Classification performance of the MFFN.

Table 6: Training and validation results.

Metrics	Training	Validation
Accuracy	99.36%	98.90%
Loss	0.1072	0.1140

3.2 Experimental Results

The MFFN model was trained with an apple dataset for four classes. These classes contain different types



(a) Training and validation accuracy

(b) Training and validation loss

Figure 5: Training and validation results.

of apple leaf diseases including Black Rot disease, Cedar Rust disease, and Scab disease. Our model was trained for 100 epochs to achieve the best accuracy in training and validation. The outcomes of the assessment highlighted areas in need of development, offered insightful information about the model's functionality, and improved it even further. Finally, the performance review showed that our suggested model is a strong solution in its field and very successful at accomplishing the aims it set out to do.

The preciseness of the training and validation of the suggested model demonstrated remarkable accuracy. The model performed well, as evidenced by the average training and validation accuracy of 99.36% and 98.90%, respectively. Furthermore, it was noted that the model's thoroughness was further supported by the training and validation losses, which were 0.1072 and 0.1140, respectively. Figure 5 and Table 6 indicate that our proposed model achieved the best performance during training on the apple plant village dataset for apple diseases classification.

3.3 Model Performance

The efficiency of the proposed MFFN model has been compared with other multi-scale CNN models to confirm its performance. Each model is trained while maintaining the aforementioned experimental procedure and experimental setting, and the outcomes are shown in Table 7. Our model demonstrates an excellent stability, as demonstrated by its high initial identification accuracy, low error rate, and rapid convergence throughout both training and validation.

Improvements have been observed in the disease classification of Apple leaves using deep learning techniques. The suggested approach represents a major advancement in the detection and classification of Apple leaf diseases, enabling precise and effective results. It is worthwhile to note that the recommended model can be made even better by adding more data sources, adjusting hyperparameters, and investigating cutting-edge deep learning architectures.

3.4 Comparison Between Different Approaches and Our Proposed Model

To examine the effectiveness and performance of the proposed MFFN, we compare our model with 10 other techniques that are used to classify Apple leaf diseases. The outcomes are contrasted with those of other pre-trained models, such as the built exclusively model. Table 8 provides an overview of the findings. From the table we find out that our suggested method performs significantly better than pre-trained models and built models. From the comparison between the techniques and MFFN in Table 8, we observed that our provided MFFN model has an accuracy rate higher than the other architectures in the field of Apple leaf diseases classification.

4 CONCLUSION AND FUTURE WORKS

Apple leaf diseases can significantly affect productivity and quality by causing early fruit drops and compromising the appearance, size, and flavor of the fruit. This can lead to financial losses for farmers and a reduction in the overall quality of apple consumption. As a result, it can lead to the economic decline of the agricultural industry. Therefore, early diagnosis of apple leaf disease and preventative mea-

Table 7: MFFN performance compared with various multi-scale CNN.

Reference	Plant	Methodology	Accuracy
Ren et al. (Ren et al., 2023)	Apple	Multi-scale parallel fusion	97.20%
Ahmed et al. (Ahmed et al., 2022)	Apple	Multi-Contextual Feature Fusion Network	90.86%
Luo et al. (Luo et al., 2021)	Apple	Multi-scale extraction of disease features	94.23%
Suo et al. (Suo et al., 2022)	Grape	Multi-scale fusion module	95.95%
Tian et al. (Tian et al., 2022)	Apple	Multi-scale feature extraction	83.19%
Proposed MFFN	Apple	Our proposed model	98.28%

Table 8: Comparison between different approaches and our proposed model on Apple leaf diseases.

Reference	Methodology	Plant	Accuracy
Zhang et al. (Zhang et al., 2021)	ResNet34	Apple	93.76%
Sangeetha et al. (Sangeetha et al., 2022)	VGG16	Apple	93.30%
Zhao et al. (Zhao and Huang, 2023)	CBAM-ENetV2 Network	Apple	97.49%
Alsayed et al. (Alsayed et al., 2021)	ResNetV2	Apple	94.00%
Sheng et al. (Sheng et al., 2022)	MobileViT-based	Apple	96.76%
Rehman et al. (Rehman et al., 2021)	Mask RCNN	Apple	96.60%
Chakraborty et al. (Chakraborty et al., 2021)	SVM	Apple	96.00%
Assad et al. (Assad et al., 2023)	AppleNet	Apple	96.00%
Chen et al. (Chen et al., 2023)	ResNet	Apple	97.78%
Yu et al. (Yu et al., 2022)	ResNet-50	Apple	95.70%
Proposed MFFN	MFFN	Apple	98.28%

sures can reduce the economic loss. Multiscale CNNs can enhance apple leaf disease classification by analyzing local and global features. They accommodate size variability in lesions, handle texture changes, and make the model more robust to real-world variations. Therefore, we utilized deep learning based on a multi-scale CNN approach to identify apple leaf diseases with a high test accuracy rate of 98.28%. The demonstrated method has shown significant and robust results in evaluation metrics such as precision, recall, and F1-score. After applying a deep learning model to the apple leaf dataset to detect apple leaf diseases in their earlier stages and achieving promising results, this simulation can be deployed as a web- or mobile-based application. Such applications will help farmers detect apple leaf diseases in real life. In future works, our proposed multi-scale CNN technique can be implemented to classify different plant species. Besides, it could be employed to identify other apple leaf diseases, making it easier for farmers and producers to categorize multiple diseases. Overall, the implementation of the proposed model may help farmers make better-informed decisions.

REFERENCES

Ahmed, M. R., Ashrafi, A. F., Ahmed, R. U., and Ahmed, T. (2022). Mcffa-net: Multi-contextual feature fusion and attention guided network for apple foliar disease classification. In *2022 25th International Conference on Computer and Information Technology (ICCIT)*, pages 757–762. IEEE.

Alsayed, A., Alsabei, A., and Arif, M. (2021). Classification of apple tree leaves diseases using deep learning methods. *International Journal of Computer Science & Network Security*, 21(7):324–330.

Assad, A., Bhat, M. R., Bhat, Z., Ahanger, A. N., Kundroo, M., Dar, R. A., Ahanger, A. B., Dar, B., et al. (2023). Apple diseases: detection and classification using transfer learning. *Quality Assurance and Safety of Crops & Foods*, 15(SP1):27–37.

Baranwal, S., Khandelwal, S., and Arora, A. (2019). Deep learning convolutional neural network for apple leaves disease detection. In *Proceedings of International Conference on Sustainable Computing in Science, Technology & Management (SUSCOM-2019)*, pages 260–267.

Barbedo, J. G. (2018). Factors influencing the use of deep learning for plant disease recognition. *Biosystems Engineering*, 172:84–91.

Chakraborty, S., Paul, S., and Rahat-uz Zaman, M. (2021). Prediction of apple leaf diseases using multiclass support vector machine. In *2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, pages 147–151.

Chen, Y., Pan, J., and Wu, Q. (2023). Apple leaf disease identification via improved cyclegan and convolutional neural network. *Soft Computing*, 27(14):9773–9786.

Divakar, S., Bhattacharjee, A., and Priyadarshini, R. (2021). Smote-dl: A deep learning based plant disease detection method. In *6th International Conference for Convergence in Technology (I2CT)*, pages 1–6.

Doutoum, A. S. and Tugrul, B. (2023). A review of leaf diseases detection and classification by deep learning. *IEEE Access*, 11:119219–119230.

Elizar, E., Zulkifley, M. A., Muharar, R., Zaman, M. H. M., and Mustaza, S. M. (2022). A review on multiscale-deep-learning applications. *Sensors*, 22(19):7384.

Gündüz, H. and Yılmaz Gündüz, S. (2022). Plant disease classification using ensemble deep learning. In *2022 30th Signal Processing and Communications Applications Conference (SIU)*, pages 1–4.

Hughes, D. P. and Salathé, M. (2015). An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. *CoRR*, abs/1511.08060.

Luo, Y., Sun, J., Shen, J., Wu, X., Wang, L., and Zhu, W. (2021). Apple leaf disease recognition and sub-class categorization based on improved multi-scale feature fusion network. *IEEE Access*, 9:95517–95527.

Nandhini, S. and Ashokkumar, K. (2022). An automatic plant leaf disease identification using densenet-121 architecture with a mutation-based henry gas solubility optimization algorithm. *Neural Computing and Applications*, 34(7):5513–5534.

Rehman, Z. U., Khan, M. A., Ahmed, F., Damaševičius, R., Naqvi, S. R., Nisar, W., and Javed, K. (2021). Recognizing apple leaf diseases using a novel parallel real-time processing framework based on mask rcnn and transfer learning: An application for smart agriculture. *IET Image Processing*, 15(10):2157–2168.

Ren, H., Chen, W., Liu, P., Tang, R., Wang, J., and Ge, C. (2023). Multi-scale parallel fusion convolution network for crop disease identification. In *2023 8th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, pages 481–485. IEEE.

Sangeetha, K., Rima, P., Kumar, P., Preethees, S., et al. (2022). Apple leaf disease detection using deep learning. In *6th International Conference on Computing Methodologies and Communication (ICCMC)*, pages 1063–1067.

Sheng, X., Wang, F., Ruan, H., Fan, Y., Zheng, J., Zhang, Y., and Lyu, C. (2022). Disease diagnostic method based on cascade backbone network for apple leaf disease classification. *Frontiers in Plant Science*, 13:994227.

Su, J., Zhang, M., and Yu, W. (2022). An identification method of apple leaf disease based on transfer learning. In *7th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, pages 478–482.

Suo, J., Zhan, J., Zhou, G., Chen, A., Hu, Y., Huang, W., Cai, W., Hu, Y., and Li, L. (2022). Casm-amfmnet: A network based on coordinate attention shuffle mechanism and asymmetric multi-scale fusion module for classification of grape leaf diseases. *Frontiers in Plant Science*, 13:846767.

Tian, L., Zhang, H., Liu, B., Zhang, J., Duan, N., Yuan, A., and Huo, Y. (2022). Vmf-ssd: A novel v-space based multi-scale feature fusion ssd for apple leaf disease detection. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*.

Yadav, A., Thakur, U., Saxena, R., Pal, V., Bhateja, V., and Lin, J. C.-W. (2022). Afd-net: Apple foliar disease multi classification using deep learning on plant pathology dataset. *Plant and Soil*, 477(1):595–611.

Yan, Q., Yang, B., Wang, W., Wang, B., Chen, P., and Zhang, J. (2020). Apple leaf diseases recognition based on an improved convolutional neural network. *Sensors*, 20(12):3535.

Yu, H., Cheng, X., Chen, C., Heidari, A. A., Liu, J., Cai, Z., and Chen, H. (2022). Apple leaf disease recognition method with improved residual network. *Multimedia Tools and Applications*, 81(6):7759–7782.

Zhang, D., Yang, H., and Cao, J. (2021). Identify apple leaf diseases using deep learning algorithm. *arXiv preprint arXiv:2107.12598*, abs/2107.12598.

Zhao, G. and Huang, X. (2023). Apple leaf disease recognition based on improved convolutional neural network with an attention mechanism. In *5th International Conference on Natural Language Processing (ICNLP)*, pages 98–102.