Detecting the Simultaneous Occurrence of Strawberry Fungal Leaf Diseases with a Deep Normalized CNN

Deperias Kerre*
Strathmore University, School of Computing and Engineering Sciences, Nairobi-Kenya

Henry Muchiri†
Strathmore University, School of Computing and Engineering Sciences, Nairobi-Kenya

ABSTRACT

Crop diseases are a major threat to food security and economic development, but their rapid identification remains difficult. Strawberry is one of the cash crops grown in Kenya and has a substantial contribution to the country's income with 50% of the foreign earnings from the horticultural crops being attributed to this crop. However, strawberry farming in Kenya has been adversely affected by the prevalence of strawberry fungal leaf diseases mainly leaf Blight and leaf Scorch which occur and affect the strawberry leaves simultaneously. A review of existing computer vision models that have been leveraged for the detection of these diseases discovered that none of the models has the capability to detect leaf Blight and leaf Scorch diseases especially when they occur simultaneously on the same leaf. This makes their detection a challenge. In this paper, we present a deep Convolutional Neural Network (CNN) model for detecting the simultaneous occurrence of Strawberry Leaf Spot and Leaf Blight. The model presents a novel technique of detecting more than a single class of the strawberry fungal diseases on the same leaf. A dataset containing a total of 1,134 images was used in training and evaluating the model. The model achieved an accuracy of 98%, precision of 98.9%, a recall of 93.3% and an f1-score of 95.9% overall thus demonstrating the feasibility of this approach. The performance of the CNN model was also compared with that of other machine learning algorithms which include Support Vector Machine(SVM), K-Nearest Neighbor(KNN) and the Random Forest. The comparison also included the other existing CNN architectures which are GoogleNet, Resnet and VGG.

CCS CONCEPTS

• **CCS Concepts**; • **Computing methodologies**; • **Machine Learning**; • **Machine Learning Approaches**; • **Neural Networks**;

KEYWORDS

Computer Vision, Convolutional Neural Network, Deep Learning, Strawberry Fungal Leaf Disease Detection

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1 INTRODUCTION

Strawberry farming is one of the most profitable economic ventures in the Kenyan economy. The crop is grown for both export and local consumption. The high value of this crop has led to increased production, marketing, and consumption of this crop over the past few years hence availing a great opportunity for income generation and employment creation [1]. Strawberry farming in Kenya has been affected by the prevalence of strawberry fungal leaf diseases mainly Leaf Scorch and Leaf Blight. The diseases have resulted to 19% loss to the famers. [2]. This is attributed to the fact that these disease categories occur on the same leaf hence making it difficult to detect them with a naked eye. The result of this is misdiagnosis of the disease categories hence applying wrong control measures which eventually leads to losses as the diseases damage the crops. The problem of disease detection is more pronounced in rural areas where observation is the commonly used method of plant disease detection. There is therefore the need for an efficient approach in detecting more than one category of strawberry fungal diseases occurring on the same leaf.

The paper gives a review of the related works regarding our proposed model. We have discussed about the materials and methods used in the implementations. Experimental results together with the comparison of the model's performance with other machine learning algorithms are described together with the conclusion and future works also featured.

2 LITERATURE REVIEW

2.1 Strawberry Fungal Leaf Disease Detection Approaches

In this section, we review some of the Computer Vison techniques that have been leveraged. The methods include those based on traditional computer vision and those based on deep learning/Convolutional Neural Network Models. Computer vision is a scientific field that deals with how to design computers to gain a higher-level understanding from digital images or videos. [3].

A model for detecting strawberry fungal leaf diseases based on a fuzzy classifier was proposed [4]. The fuzzy classifier consists of two processes: the first one is for detecting the infected and heathy leaf area based on a color processing detection algorithm (CPDA) and the second process consists of a decision-making unit based on a fuzzy classification algorithm. The optimized fuzzy parameters achieved 96% accuracy for segmented iron deficiency and 93% for fungal infection.

An evaluation of the performance of the state-of-the-art CNN architectures using the plantVillage dataset has also been done [5]. This dataset contains 54,323 images with 38 classes of various plant diseases including strawberry. The model was trained to differentiate between the plant leaves and the environment using a background class consisting of 715 images. The Stanford public dataset was used to create the background class. The integrated dataset including the background class consists of 55038 images with 39 classes. The model's evaluation achieved the following results: Training from scratch (80-20% train-test distribution), AlexNet-accuracy of 97.82% and GoogleNet -accuracy of 98.36%. The results for transfer learning were as follows: AlexNet – accuracy of 99.24% and GoogleNet -accuracy of 99.34%. Inception v3 achieved the best accuracy of 99.72% through transfer learning. A deep learning model for plant disease detection called plant disease detector was also proposed by another study [6]. The model was based on a CNN where two datasets were used to train and evaluate the model. The final work was based on the plant village dataset. The model achieved 98.3% testing accuracy and an accuracy of 95% when tested on 100 actual environment images. Another study proposed a CNN model for plant disease detection using a dataset with 54,306 images of plant leaves, containing 38 classes [7]. Each class pair was constituted a crop - disease pair which was used to predict the crop-disease class. The model was implemented in AlexNet and GoogLeNet architectures and a comparison between them was made. The model achieved an accuracy of 85.53% and 99.34% for AlexNet architecture for training form scratch and using transfer learning, respectively.

Author [8] proposed a deep learning model to automate the plant diseases detection using an open access database containing 87,848 images, with 58 distinct classes of [plant, disease] combinations of both healthy and unhealthy leaves. Strawberry leaf scorch was one of the disease classes covered. The best performance of this in plant disease detection was 99.53%. Lastly, a CNN model based on the Resnet50 architecture for the detection of strawberry leaf blight, gray mold and powdery mildew was also proposed [9]. The model achieved an accuracy of 98.06% and 99.60% for original and feature datasets respectively. Another study proposed an improved approach for detecting strawberry leaf diseases. A backbone feature extractor dubbed plant Net was used and the model achieved ana accuracy of 91.65% [10].

From the review of the related works, several key observations are made: The model based on fuzzy logic could be improved to consider the detection of the simultaneous occurrence of the different classes of the fungal diseases on the same leaf [4]. Despite the success rate of the various deep learning models, they covered only two classes of the fungal leaf diseases: Leaf Blight and Leaf Scorch. The models did not therefore consider a scenario where more than one class of the fungal diseases occur on the same leaf hence not suitable for the detection of the simultaneous occurrence of strawberry the fungal diseases. Most of the datasets used by the deep learning models do not consider a scenario where multiple strawberry fungal leaf diseases occur on the same leaf[5-10]. In summary, there is need to develop a methodology that considers the detection of more than one class of the fungal leaf diseases on the same leaf. This will assist in the control of these diseases as the appropriate measures will be applied to them. Some of the fungal diseases have close signs hence the complexity of their detection increases when they occur on the same leaf. There is also the need to collect more data that contains instances where multiple disease classes affect the same leaf to enhance research in their detection.

Figure 1: Healthy Leaf

Figure 2: Leaf Infected by both Leaf Blight and Leaf Scorch

Figure 3: Leaf Spot

3 MATERIALS AND METHODS

3.1 Dataset

The data used in this study consisted of both primary and secondary data. Primary data consisted of 75 images taken from strawberry farms in Kinangop, Central Kenya. The images were taken using a Sony RX1R II Professional Compact Camera with a 35mm Sensor and 42.4 MP resolution. They were taken in varying positions and consisted of both healthy and diseased leaves. Secondary data consisted of images obtained online from the PlantVillage dataset repository available at Kaggle. The image dataset constituted a total of 1,134 images. The dataset was divided as follows:80%(420 images) for training and 20% (105 images) for validation. Table 1 shows a summary of the image dataset. Figure 1, Figure 2, Figure 3, Figure 4 ,Figure 5 shows sample leaves with the various disease classes.

3.2 Detection Methodology

The CNN based model was developed as follows:

Table 1: Summary of the Image Dataset

Disease Class	Number of Images
Strawberry Healthy	450
Strawberry Leaf Scorch	450
Strawberry Leaf Blight	74
Strawberry Leaf Spot	85
Strawberry Leaf Blight and Leaf Scorch	75
Total	**1,134**

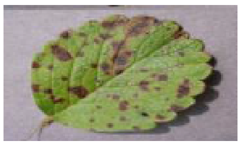

Figure 4: Leaf Scorch

Figure 5: : Leaf Blight

3.2.1 Data Preprocessing. Data pre-processing was carried out before channeling the dataset to the model for training. The two processes that were carried out under this phase are data standardization and data augmentation. Data standardization involved resizing all the images to a standard size of 256 X 256 using PIL(Python Imaging Library). This was important in ensuring all the images fits the input shape of the deep learning model. The image augmentation techniques used in this study included flipping, rotation, cropping, zoom, shear [11]. Data augmentation is also important in minimizing the overfitting effect that normally affects the performance of many machine learning models. Data augmentation was implemented by creating an object of the Keras ImageDataGenerator() class containing the specified transformations for data augmentation. This was later passed to the model as input during training. The ImageDataGenerator class inflates input images with an infinite number of transformations hence availing more features for training [12].

3.2.2 Model Design and Training. The Strawberry fungal disease detection model was based on a normalized sequential Convolutional Neural Network. The model was developed from scratch using the Google Colab as the development environment. The platform provided a free access to the GPU which was important in accelerating the model training. Table 2 shows the software and hardware resources used for model development and training.

The model was defaulted to the " channel_first" architecture and also a switch for backends that support "channel_last" . The architecture consisted of 2D Convolutional layer with 32 filters of 3 x 3 kernel and a ReLU (Rectified Linear Unit) activation. Batch normalization, max pooling and 25%(0.25) followed in the subsequent layers. Two blocks of 2D Convolutional layer with 64 filters and ReLU activation followed by a pooling and dropout layer. This step was repeated for the last set of fully connected layers with 128 filters with the Conv2D layer being the only difference. SoftMax activation was used in the final layer. The general model implementation was done with multiple pooling and convolutional layers with a dense layer to be used for the prediction task**.** The parameters for the model configuration were as follows: a batch size of 32, 30 Epochs, the number of training steps set to 100, a learning rate of 1e-3, a depth of 3 and the image width and height set to a size of 256. The parameters were chosen on an experimental basis. Table 3 shows the experimental results of the parameters.

Our CNN model was also developed with a normalization of the activations of the intermediate layers of the deep neural network. This technique has an effect of improving model accuracy and speeding up the training process. With batch normalized networks, the overfitting effect can either be removed or reduced in strength . Previous studies hints that that Batch Normalization primarily enables training with larger learning rates, which enhances faster convergence and better generalization in deep learning models [13]. 4 shows the parameters used for training the model which were determined on am experimental basis. Figure 6 shows the proposed model.

4 RESULTS AND DISCUSSIONS

4.1 The CNN Model Performance

Our main objective was to design a deep learning model that can detect the simultaneous occurrence of Strawberry Leaf Scotch and Leaf Blight. The detection of these classes of diseases increases in complexity when they occur on the same leaf. The model therefore needs to accurately learn the overlapping features in order to detect them. The deep learning model's performance during training is as shown in Figure 7 and Figure 8

From Figure 7, the model validation accuracy was lower than the training accuracy at the beginning and increased with the training progress. The training accuracy denotes the performance of the model on the training dataset while the validation accuracy denotes the model's performance on the testing dataset. The small gap

Table 2: Model Hardware and Software Resources

Parameter Type		Description
Hardware		
Google Cloud	GPU	1xTesla K80, having 2496 CUDA cores, compute 3.7, 12GB (11.439GB Usable) GDDR5 VRAM
	CPU	1xsingle core hyper threaded i.e. (1 core, 2 threads) Xeon Processors @2.3Ghz
	RAM	12.6 GB
	Disk	320 GB
Software		
Development Language	Python 3.8	

Table 3: Training Parameters Results

	Hyper Parameter	Results
Learning Rate		
	0.00001	Longer training period of 2465 seconds Accuracy of 66.86%
	0.0001	Training period of 1872 seconds Converged to a non-optimal accuracy of 65.34 %
	0.001	Optimal accuracy of 98% with an optimal training time of 1400 seconds
Number of Epochs		
	20	Accuracy of 89.15%
	30	Accuracy of 98.4%
	40	Accuracy of 87.16%

Table 4: Model Training Parameters

Parameter	Value
Number of Epochs	30
Batch Size	32
Activation in the middle layers	Relu
Activation in the final layer	Softmax
Learning Rate	1e-3

between the two accuracies in the last epoch signifies minimal overfitting effect being exhibited by the model. Figure 8 shows the model training and validation losses. Loss represents the sum of errors made for each sample data in the training and validation sets. The two losses decreased to a point of stability between the 15th and the 20th epochs with no gap between them in the last epoch. The dips are attributed to lower generalization capability in the initial training phases which increased throughout the training process. This indicates that the model was a good fit on the validation dataset/generalized well.

Model validation was done on the 20% validation dataset. This constituted a total of 226 images where 90 images were for strawberry healthy, 14 for strawberry leaf blight, 90 for leaf scorch, 17 for leaf spot and 15 images for leaf blight and leaf scorch. Table 5 shows the confusion matrix which indicates the performance of the model.

Out of a total of 226 images presented to the model, 222 images were correctly classified into the respective disease classes hence resulting to an accuracy of 98%. This is the general performance of the model for all the categories considered. This implies that around 98% of the images presented to the model were correctly classified into the respective fungal disease classes. The detection of the simultaneous occurrence of Leaf Blight and Leaf Scorch was done well by the model, achieving an accuracy of 86.67%(13 images out 15 correctly classified by the model). These are promising results for the future of detecting the simultaneous occurrence of the fungal

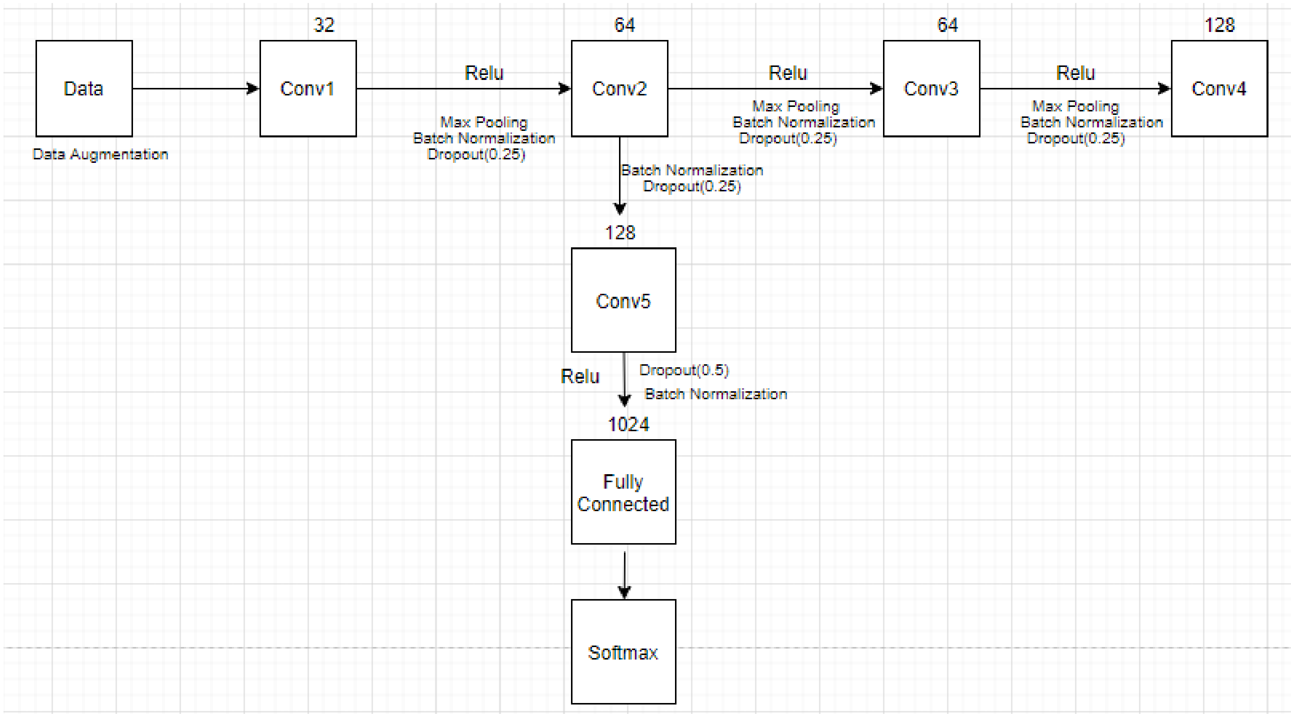

Figure 6: The proposed Model

Table 5: The Confusion Matrix for the proposed Deep Learning Model

Actual Label/Predicted Label	Healthy	Leaf Blight	Leaf Scorch	Leaf Scorch and Leaf Blight	Leaf Spot	Accuracy per class
Healthy	89	1	0	0	0	98.89%
Leaf Blight	0	14	0	0	0	100%
Leaf Scorch	0	0	90	0	0	100%
Leaf Scorch and Leaf Blight	0	0	2	13	0	86.67%
Leaf Spot	0	1	0	0	16	94.12%

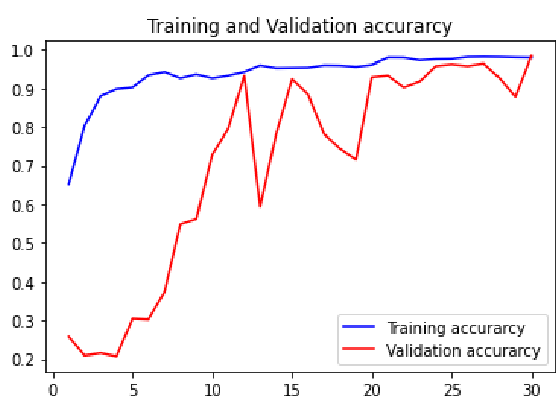

Figure 7: Training and Validation accuracy against the number of epochs

diseases. The other metrics used to evaluate the model includes the precision, recall and the f1-score. The classification report is as shown in Table 6

From Table 6, the results were as follows: an aggregated precision of 0.971, a recall of 0.959 and an f1-score of 0.963. A precision of 0.971 implies that 97% of the prediction results returned by the model were relevant/correct. This indicates a good proportion of the relevant results by the model. The aggregate recall of 0.959 indicates a good performance of the model in correctly identifying the relevant instances of the disease classes. An aggregate f1-score of 0.963 achieved by the model implies that the model achieved both higher recall and precision as f1-score is the harmonic mean of the two. This results to a good accuracy in making the predictions.

Table 6: Classification Report

	Precision	Recall	F1-Score	Support
Strawberry Healthy	1.000	0.989	0.994	90
Strawberry Leaf Blight	0.875	1.000	0.933	14
Strawberry Leaf Scorch	0.978	1.000	0.989	90
Strawberry Leaf Scorch and Leaf Blight	1.000	0.867	0.929	15
Strawberry Leaf Spot	1.000	0.941	0.970	17
Accuracy			0.982	226
Macro Avg	0.971	0..959	0.963	226
Weighted Avg	0.984	0.982	0.982	226

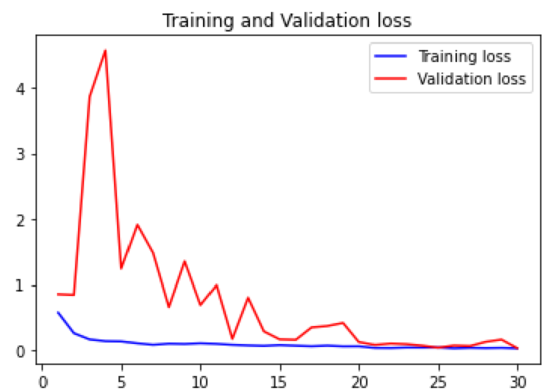

Figure 8: Training and Validation loss against the number of epochs

Table 7: KNN Results

Metric	Value(%)
Accuracy	57.58
Precision	55.36
Recall	53.84
F1-Score	54.59

4.2 Comparison with other Machine Learning Algorithms

Other machine learning algorithms were also used for the prediction task for comparison purposes. These include the K-Nearest Neighbor(KNN), Support Vector Machine(SVM) and the Random Forest. These classifiers were developed using the Scikit-learn API. Table 7, Table 8 and Table 9 shows the results for K-Nearest Neighbor(KNN), Support Vector Machine(SVM) and the Random Forest respectively.

The comparison of the performance of the proposed CNN model with the other machine learning algorithms clearly depicts the greater performance the CNN model. This is attributed to the model' s ability to learn the complex features used in the classification of the simultaneously occurring fungal diseases. The higher performance of the model signifies its ability to model and learn the overlapping fungal leaf diseases features occurring on the same leaf. This architectures input consists of an image size of 224 X224. The structure consists of 1x1, 3 x3, 5 x5 convolution kernels and a 3 x3 pooling layer that performs parallel operations at the same time. In this structure, all the convolved feature images overlap to generate a new feature image after the parallel operations are completed. The Resnet50 model on the other hand, won the 2015 ILSVRC image classification championship. This model has a residual network layer. The model's architecture consists of 5 convolution layers. The model aims to reduce the problem of degradation during calculation. This is achieved by having the roll machine layer learns new features during feature input .The Vgg16 model won the runner-up in the 2014 ImageNet image classification competition. It inherited the 2012 AlexNet network design ideas. As a result, increased from eight to 16 layers on the AlexNet network. It therefore consists of 13 convolutional layers (Conv), five pooling layers (Pooling), and three fully connected layers (gray parts). The above CNN models' implementation and training was done in Python on the Google Colab platform. The training was done using an 80:20 ratio for training and testing respectively. The training parameters adopted are as shown in Table 4. Data augmentation was also used to minimize the problem of overfitting when there is limited training data. The corresponding training accuracies were recorded for the three models. The general validation accuracy rates for VGG-16, GoogLeNet, and Resnet-50 were 94.69%, 88.50%, and 88.94%, respectively. The models' performance per disease class is shown by the confusion matrices in Table 10, Table 11 and Table 12

Table 8: SVM Results

Metric	Value
Accuracy	72.64
Precision	83.46
Recall	67.81
F1-Score	74.83

From the models' performance in each disease classes shown in Table 11,Table 11 and Table 12, GoogleNet presents a better accuracy of 80% for the detection of simultaneous occurrence of Leaf Blight and Leaf Scorch. This is followed by VGG 16(73.33%) and finally

Table 9: Random Forest Results

Metric	Value
Accuracy	78.14
Precision	82.67
Recall	76.16
F1-Score	79.28

Table 10: The confusion matrix for VGG 16

Actual Label/Predicted Label	Healthy	Leaf Blight	Leaf Scorch	Leaf Scorch and Leaf Blight	Leaf Spot	Accuracy per class
Healthy	88	2	0	0	0	97.78%
Leaf Blight	0	13	0	1	0	92.86%
Leaf Scorch	2	0	86	2	0	95.56%
Leaf Scorch and Leaf Blight	0	2	2	11	0	73.33%
Leaf Spot	1		0	0	16	94.12%

Table 11: The confusion matrix for GoogleNet

Actual Label/Predicted Label	Healthy	Leaf Blight	Leaf Scorch	Leaf Scorch and Leaf Blight	Leaf Spot	Accuracy per class
Healthy	84	2	2	0	4	93.33%
Leaf Blight		11	0	3	0	78.57%
Leaf Scorch	3	0	83	2	2	92.22%
Leaf Scorch and Leaf Blight	1	2	2	10	0	66.67%
Leaf Spot	4		0	0	13	76.47%

Table 12: The confusion matrix for Resnet 50

Actual Label/Predicted Label	Healthy	Leaf Blight	Leaf Scorch	Leaf Scorch and Leaf Blight	Leaf Spot	Accuracy per class
Healthy	82	2	2	0	4	91.11%
Leaf Blight	2	10	0	2	0	71.43%
Leaf Scorch	5	0	81	2	2	90.00%
Leaf Scorch and Leaf Blight	0	1	2	12	0	80.00%
Leaf Spot	2		0	0	15	88.24%

Resnet 50 (66.67%). This clearly depicts the promising ability of the proposed normalized CNN model.

5 CONCLUSION

In this paper, the main objective was to develop a mechanism automate the detection of the simultaneous occurrence of strawberry fungal leaf diseases mainly for the simultaneous occurrence of Strawberry Leaf Blight and Leaf Scorch .The disease class prediction mechanism developed was based on the feature extraction capabilities of a normalized CNN. The model was developed using both primary and secondary data consisting of 1,134 images. The model achieved an accuracy of 98 % generally for all classes considered and 86.67% for the simultaneous occurrence of leaf blight and leaf scorch. The accuracy denotes good performance of the model in the detection of the simultaneous occurrence of Strawberry leaf scorch and leaf blight which provides a good foundation for future research in detection of several fungal diseases affecting the same part of the plant. The data collected by the study contributes to the existing data repositories hence enhancing research in the detection of the simultaneous occurrence of strawberry fungal leaf diseases. A comparison of the model's performance with the other machine learning algorithms clearly depicts the model's ability to model the overlapping disease features. Based on the performance of the model, it can be concluded that CNNs can be used for the detection of the simultaneous occurrence of strawberry fungal leaf diseases such as Leaf blight and leaf scorch. More effort is needed to collect more data with instances where disease classes occur simultaneously on the same leaf as this will enhance research in their detection.

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REFERENCES

[1] Mwangi, M., Egesa, A., & Matheri, F. (2016, August). Strategies to increase strawberry competitiveness among fruit growers, marketers and consumers in Kenya. In VIII International Strawberry Symposium 1156 (pp. 921-928).

[2] Egesa, A. O., Njeri, N., Matheri, F., Mwirigi, P., & Mwangi, M. 3.3 Challenges facing strawberry farming in central Kenya. In 2nd biennial international conference on enhancing sustainable agricultural production and marketing systems (Vol. 38, No. 1, p. 133).

[3] Jähne, B., & Haussecker, H. (2000). Performance characteristics of low-level motion estimators in spatiotemporal images. In Performance Characterization in Computer Vision (pp. 139-152). Springer, Dordrecht.

[4] Kiani, E., & Mamedov, T. (2017). Identification of plant disease infection using soft computing: Application to modern botany. Procedia computer science, 120, 893-900.

[5] Chohan, M., Khan, A., Chohan, R., Hassan, S., & Mahar, M. (2020). Plant disease detection using deep learning. International Journal of Recent Technology and Engineering, 9(1), 909-914.

[6] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.

[7] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318.

[8] Fang, T., Chen, P., Zhang, J., & Wang, B. (2020). Crop leaf disease grade identification based on an improved convolutional neural network. Journal of Electronic Imaging, 29(1), 013004.

[9] Xiao, J. R., Chung, P. C., Wu, H. Y., Phan, Q. H., Yeh, J. L. A., & Hou, M. T. K. (2021). Detection of Strawberry Diseases Using a Convolutional Neural Network. Plants, 10(1), 31.

[10] Kim, B., Han, Y. K., Park, J. H., & Lee, J. (2021). Improved vision-based detection of strawberry diseases using a deep neural network. *Frontiers in Plant Science*, *11*, 2040.

[11] Taylor, L., & Nitschke, G. (2018, November). Improving deep learning with generic data augmentation. In 2018 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 1542-1547). IEEE.

[12] Chollet, F. (2016). Building powerful image classification models using very little data. Keras Blog, 5.

[13] Bjorck, J., Gomes, C., Selman, B., & Weinberger, K. Q. (2018). Understanding batch normalization. arXiv preprint arXiv:1806.