Hindawi
Journal of Food Quality
Volume 2022, Article ID 9211700, 12 pages
https://doi.org/10.1155/2022/9211700

Research Article

Design and Evaluation of a Hybrid Technique for Detecting Sunflower Leaf Disease Using Deep Learning Approach

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Received 8 January 2022; Revised 22 February 2022; Accepted 10 March 2022; Published 8 April 2022

Academic Editor: Muhammad Faisal Manzoor

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Agriculture and plants, which are a component of a nation's internal economy, play an important role in boosting the economy of that country. It becomes critical to preserve plants from infection at an early stage in order to be able to treat them. Previously, recognition and classification were carried out by hand, but this was a time-consuming operation. Nowadays, deep learning algorithms are frequently employed for recognition and classification tasks. As a result, this manuscript investigates the diseases of sunflower leaves, specifically *Alternaria* leaf blight, *Phoma* blight, downy mildew, and *Verticillium* wilt, and proposes a hybrid model for the recognition and classification of sunflower diseases using deep learning techniques. VGG-16 and MobileNet are two transfer learning models that are used for classification purposes, and the stacking ensemble learning approach is used to merge them or create a hybrid model from the two models. This work makes use of a data set that was built by the author with the assistance of Google Images and comprises 329 images of sunflowers divided into five categories. On the basis of accuracy, a comparison is made between several existing deep learning models and the proposed model using the same data set as the original comparison.

1. Introduction

Sunflower originated in 2100 BCE in Mexico, and it is also known as *Helianthus*. Sunflower seeds and their leaves have several uses and benefits. Sunflower can be used for food because it has many nutrients in its seeds and leaves. Sunflower roots have the soaking ability by which it is able to soak the radioactive substance too. It is also a good source of vitamins. Due to its therapeutic properties, sunflower is also used in the treatment of various diseases such as malaria, arthritis by reducing swelling, gastroenteritis, chest pain, and respiratory tract disorders. Sunflower leaves have properties that can cure insect bites, snake bites, spider bites, headaches, etc. Its leaves have diuretic properties by which it can cure bladder disorders, and it can also act as an antioxidant. Sunflower leaves have several uses in animal husbandry and many industries. Sunflower leaves are affected by many diseases, but in this thesis, *Alternaria* leaf blight, *Phoma* blight, downy mildew, and *Verticillium* wilt are considered:

Alternaria leaf blight: *Alternaria helianthi* is the fungal plant pathogen responsible for *Alternaria* leaf blight, as shown in Figure 1. South Africa is the major area of *Alternaria* diseases. It is a potential disease occurring in the producing areas of sunflower.

Symptoms: concentric rings of 0.2–0.5 mm diameter with dark brown to black lesion appear on the leaves and stems. When the spores on the leaves or stems

Figure 1: *Alternaria* leaf blight.

Figure 2: Downy mildew.

come in the contact of moisture and start penetrating, then the infection process starts.

Treatment: fungicides are sprayed directly on infected plants, coupled with improved sanitation and crop rotation.

Downy mildew: this disease is caused by a plant pathogen called *Plasmopara halstedii*. *Plasmopara halstedii* oospores produce thin walls, which are resistant structures, sexually produced that are fundamental for its continuation, as shown in Figure 2. Entering a territory, the annihilation of the microbe is troublesome because of the arrangement of oospores, which can stay in soil for a long time.

Symptoms: initial symptoms are visible on the upper surface like large, angular or blocky, yellow areas. They rapidly expand and become brown-like lesions, mature. The under surface of infected leaves appears water-soaked.

Phoma blight: this disease is caused by the plant pathogenic fungus called *Phoma macdonaldii*, as shown in Figure 3, and it is also a common disease caused by soil-borne fungi.

Symptoms: this is perceived as a huge dull sore on the stem, begins from the leaf and reaches the petiole. The enormous patches on the tail become generally perceptible after the petal drops.
Treatment: 4-year crop rotation is a good treatment for curing *Phoma* blight, which reduces the disease by controlling stem weevil.

Verticillium wilt: *Verticillium dahliae*, a soil-borne fungus, is the main cause of the disease. It is also called "Vert," and it starts from the lower leaves and moves to the whole leaves, as shown in Figure 4.

Figure 3: *Phoma* blight.

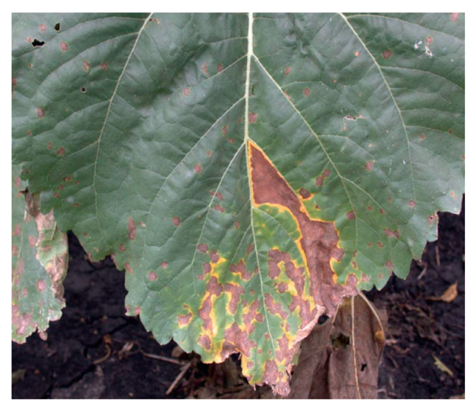

Figure 4: *Verticillium* wilt.

Sunflower and its leaves have various uses and benefits. They are beneficial for human beings, animals, and the environment; so if it gets infected, then it is a big loss to the environment. If we can identify or recognize the diseases in the initial stage, then we can save the sunflower plant and its leaves, thus saving the environment and source of many nutrients. There are some ancient methods and some computer vision methods to classify or recognize the diseases in the earlier stage.

In the past, diseases were classified manually without the use of electronic devices, which required more time, was more expensive, and had a higher chance of error because the entire process was carried out by humans. However, computer vision (also known as machine learning) has made it possible to reduce the processing time of classification and also provide better accuracy than the manual method. It is also capable of classifying multiple images at the same time. In the field of machine learning, there are three main learning approaches: supervised learning, unsupervised learning, and reinforcement learning. In machine learning, there are many different approaches, such as linear regression, decision tree, logistic regression, SVM, random forest, Naive Bayes, KNN, and k-means. Although machine learning algorithms give decent accuracy, they fall short of the target, i.e., we were unable to identify images with high accuracy when employing machine learning algorithms. When it comes to text value prediction and categorization, machine learning algorithms are the most effective tools. Deep learning began to have an influence on picture categorization at around this time.

Early identification and prediction of plant diseases is one of the most crucial needs for developing agriculture, which is important to our country's economy. It supports the economy and feeds a large population. And, by earlier detection, we can conserve the plants and avoid losses. Deep learning techniques are frequently used to classify or forecast outcomes [1, 2]. Deep learning techniques are used as active methods for the classification of plant diseases [3], and the main classifier used is convocational neural network (CNN). The CNN is one of the most recommended models for the classification or recognition with the help of images whether we have a large or small data set [4]. As deep learning dynamically analyses structured characteristics, there is no need to manually design the feature extraction function and classifier. Deep learning methods surpass machine learning as image classifiers with CNN being the best. The CNN is widely recognized as the finest and most effective image classifier on both small and large data sets, and it serves as the foundation for all deep learning models [5, 6]. It is a basic deep learning model used for the classification of images according to some patterns or features. One of the best properties is that CNN trained in a supervised manner with the help of existing data [7]. The CNN is a basic architecture over which many models are formed such as AlexNet, GoogLeNet, and LeNet. The CNN architecture is presented in Figure 5. The CNN attains the name of best image recognition system and is the most recommended system for the purpose of recognition and classification [8]. It performs well in the plant disease detection task. It is the finest technique for object identification. Any neural architecture should be able to be paired with any feature exactor, depending on the requirements. Data preprocessing is necessary for models to operate correctly. Many infections (viral or fungal) may be difficult to identify due to overlapping signs [9, 10].

Other strategies are based on ensemble learning, which is used to develop several models and then merge the models with the assistance of ensemble methods to enhance the results. Most of the time, the ensemble technique outperforms the single model in terms of performance. Some of the ensemble approaches are bagging (also known as boosting), majority voting (also known as weighted average), and stacking (also known as stacking ensemble). In this research, two approaches of ensemble learning technique—namely, stacking ensemble and weighted average technique—are applied, and the outcomes of the both are compared with one another.

2. Related Work

Zhong and Zhao [11] used the DenseNet-121 deep learning technique to classify the 6 apple diseases with three methods for which they used the data set of 2462 images, and they concluded that their proposed method gave the accuracy of 93.51%, 93.31%, and 93.71%, respectively.

Ji et al. [12] proposed a CNN based on an integrated method to classify the grape leaf diseases for which they used a data set from the PlantVillage database, and they concluded that their proposed method gave 99.17% and 98.57% accuracy for validation and test, respectively.

Uguz and Uysal [13] developed a CNN model to classify the olive leaf diseases, i.e., *Aculus olearius* and olive peacock spot disease. They used the data set of 3400 olive images from Turkey and used the transfer learning techniques, i.e., VGG-16 and VGG-19, and they concluded that their proposed model gave an accuracy of 95%.

Nanehkaran et al. [14] proposed a CNN method for the detection of leaf diseases, and they divided their method into two parts—image segmentation and image classification; they also proposed a segmentation algorithm based on intensity and LAB. They concluded that their proposed method gave a detection accuracy of 75.59%.

Jiang et al. [15] proposed the hybrid method of CNN and SVM to classify rice diseases. They used CNN for the feature extraction of disease images and then used SVM for the classification of the diseases with a 10-fold cross-validation method. They concluded that their proposed method gave a test accuracy of 96.8%.

Ghosal et al. [16] developed a CNN model with the help of VGG-16 for the classification of rice leaf diseases, and to train the model, they created their own data set of rice images and concluded that their method gave an accuracy of 92.46%.

Jasim et al. [3] proposed a method for the detection and classification of tomatoes, pepper, and potato leaf diseases. They collected 20,636 images from the PlantVillage database to make their data set. They classified 12 leaf disease classes and 3 healthy leaf classes with the help of the CNN method concluded that their model gave a training accuracy of 98.29%, and 98.029% for testing.

Md. Rasel Howlader et al. in [17] have studied guava leaf diseases, using deep CNN to see infection, and their designs characterise for important diseases, for example, algal leaf area, whitefly, and rust. They collected their own data set and even developed their own model. They conclude that their model gave an accuracy of 98.74%.

The mango leaf disease called anthracnose was managed by Singh et al. [18]. In their study, they tried to suggest a concept in addition to a monetarily savvy program for which they make use of a multilayer convolutional neural community (MCNN). They prepared their model with a continuing image on the Faculty of J&K. They concluded their unit provided an accuracy of 97.13% for sickness called anthracnose.

Geetharamani and Arun [19] proposed a disease ID type of a novel grow leaf which is determined by Deep CNN. They prepared the model of theirs with a receptive dataset of thirty-nine photos as well as groundwork photographs. This

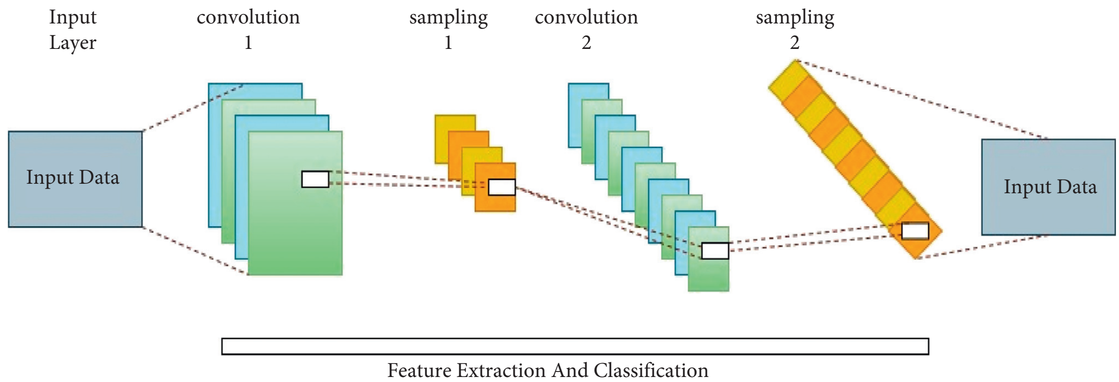

Figure 5: CNN architecture.

study includes six parameters on photos as turn, gamma remedy, clamor infusion, PCA, and scaling, and then photo flipping is utilized by them. They declared due to the exercise exhibitions on the purposed method are expanded. They contrast the model of theirs and also the previous body as well as the main reason which their unit provides much better results with 96.46% exactness.

Jiang et al. [20] took care of 5 types of infection in apple leaves by making use of the deep learning approach based on improved convolutional neural structures. Same authors prepared the model of theirs with frequent photographs of apple leaf within the wake of using a few images controlling methods. They used the GoogLeNet system in addition to upgraded CNN and the utilisation of INAR (SSD with Inception component as well as Rainbow connection) when designing a Panasonic phone. The proposed model yields 78.80 percent exactness with an excellent place velocity of 23.13 fps, which was substantially better than prior versions.

Akshay and Vani [21] made sure that the convolutional neural structure would become the greatest technique to perceive the maladies. They proposed a unit to evaluate the infection of tomato foliage and created their very own data set from the PlantVillage database. They stated that their model provided 99.25% precision. They compared their model with different neural networks such as ResNet-50, VGGNet, and also LeNet.

Hasan et al. [22] tried to find the right technique to figure out the jute diseases (chlorosis along with yellowish mosaic). Jute was selected for the very first time. They used 600 images as a data set and also inferred their proposed method provided 96% exactness without using any image-creating method.

Mohit Agarwal et al. in [23] tried to find out the diseases within apple foliage through the use of neural telephone system strategies. They released a data set from the town's grow the town initiative. They utilised a multilayer neural network to create their suggested style and also compare it to two CNN models, InceptionV3 and VGG16, to determine which model is more specific than the others and also provides 99% accuracy, as well as additionally determine which their unit captures seven seconds for screening.

A neural method to cluster the ailments of vegetation using an image was proposed by Sijiang Huang et al. in [24]. A unique deep neural network structure in this study is used that can accurately categorise plant kinds and illness using a single picture of a plant leaf. The proposed model is composed of two sub-models: a leaf segmentation model that utilises a U-Net to effectively separate the leaves in the original image from the background, and a plant disease classification model that utilises two-head network to classify plant diseases using features extracted from various popular pre-trained models. Experiments reveal that final model obtains a classification accuracy of 0.9807 for plants and a disease identification accuracy of 0.8745.

Singh [25] focused on the use of sunflower in oil production and agriculture areas. He mentioned that it is difficult to detect the damage or disease of sunflower for a full farm. Therefore, he proposed an algorithm for segmenting and classifying the images of sunflower leaf. The practical swarm optimization method is used for the classification of disease.

Sujithra and Ukrit [26] identified that it is not easy to figure out the disease on the leaf as most of the leaves are found damaged. They analyzed various deep leaning and image processing methods to classify the disease. Furthermore, it was said that neutral network algorithms like support vector help identifying and classifying leaf diseases.

Montecchia et al. [27] recognized that the soil-borne disease that affect sunflower is SVW (sunflower *Verticillium* wilt and leaf mottle). They carried out their work in infected fields of the Argentina region. This paper highlights the various disease descriptors depending on disease incidence and severity. This paper presents a way for resisting the SVW of sunflower.

Huu Quan Cap et al. in [28] ascertain that identification of growing diseases was accomplished in a couple of ways: they used only a small photo, i.e., a few of the tips of the photograph as information, and on the off chance that they used a continuous photo, they saved additional time by utilising a leaf limitation method with deep understanding. Additionally, their technical precision was 78 percent within 2.0fps.

Zhang et al. [29] dealt with the ID and also evaluation of maize leaf problems. It basically focused on the various

Table 1: Summary of various crops, their diseases, and the referred models and their accuracy.

Author	Crop	Disease	Model used	Accuracy
Yong Zhong and Ming Zhao	Apple	All disease	DenseNet-121	93.71%
Miaomio Ji et al.	Grape	Black rot, esca, and isariopsis leaf spot	CNN	99.17% (validation) and 98.57% (testing)
Sinan Uguz and Nese Uysal	Olive	*Aculus olearius* and olive peacock spot diseases	VGG-16 and VGG-19	95%
Junde Chen et al.	Plants	Common	MobileNet-V2	99.85% (public data set) and 99.11% (collected data set)
Y.A. Nanehkaran et al.	Plants	Common	CNN + LAB	75.59%
Shreya Ghosal et al.	Rice	Leaf blast, leaf blight, and brown spot	VGG-16	92.46%
Marwan Adnan Jasim et al.	Tomato, pepper, and potato	Common	CNN	98.29% (training) and 98.029% (testing)
Junde Chen et al.	Plants	Common	VGGNet + ImageNet	91.83% and 92%
Md. Rasel Howlader et al.	Guava	Whitefly, algal leaf spot, and rust	D-CNN	98.74%
Uday Pratap Singh et al.	Mango	Anthracnose	MCNN	97.13%
Geetharamani G. and Arun Pandian	Plants	Common	D-CNN	96.46%
Md. Zahid Hasan et al.	Jute	Chlorosis and yellow mosaic	CNN	96%
Sijiang Huang et al.	Plants	Common	U-Net and ResNet	98.07% (classification) and 87.45% (recognition)
S. Santhana Hari et al.	Plants	Common	CNN	86%
Sammy V. Militante et al.	Plants	Common	CNN	96.5%
Mercelin Francis and C. Deisy	Apple and tomato	Common	CNN	87%
Jayme Garcia Arnal Barbedo	Plants	Common	CNN	87%
Md. Helal Sheikh et al.	Maize and peach	Gray leaf spot corn, common rust corn, and bacterial spot peach	CNN	99.28%
Mehmet Metin Ozguven and Kemal Adem	Sugar beet	Low, severe, and low and severe	Faster R-CNN	95.48%
Malik Hashmat Shadab et al.	Sugarcane	*Cercospora* leaf spot, helminthosporium leaf spot, rust, red rot, and yellow leaf disease	YOLO + FR-CNN	93.20%
Radhamadhab dalai and Kishore Kumar Senapati	Plants	Bacterial canker, gray mold, blossom end rot, and whitefly	R-CNN	75.43%, 67.85%, 72.13%, and 49.87%
A.S.M. Farhan Al Haque et al.	Guava	Anthracnose, fruit rot, and fruit canker	CNN	95.61%
Sukhvir Kaur et al.	Plants	Common	Machine learning	—
Siddharth Singh Chouhan et al.	Plants	Common	BRBFNN	89%
Huu Quan Cap et al.	Plants	Common	CNN	78%
Robert G. de Luna et al.	Tomato	*Phoma* rot, leaf miner, and target spot	FR-CNN	91.67%
Rutu Gandhi et al.	Plants	Common	CNN + GANs	—
Konstantinos P. Feretinos	Plants	Common	VGG	99.53%
K.R. Aravind et al.	Maize	*Cercospora* leaf spot, common rust, and leaf blight	SVM	83.7%
Edna Chebet Too et al.	Plants	Common	DenseNet	99.75%
Halil Durmus et al.	Tomato	Yellow leaf curl, bacterial spot, early blight, late blight, leaf mold, Septoria leaf spot, spider mites, target spot, and mosaic virus	AlexNet and SqueezeNet	95.65% and 94.3%
Usama Mokhtar et al.	Tomato	Powdery mildew and early bright	SVM	99.5%

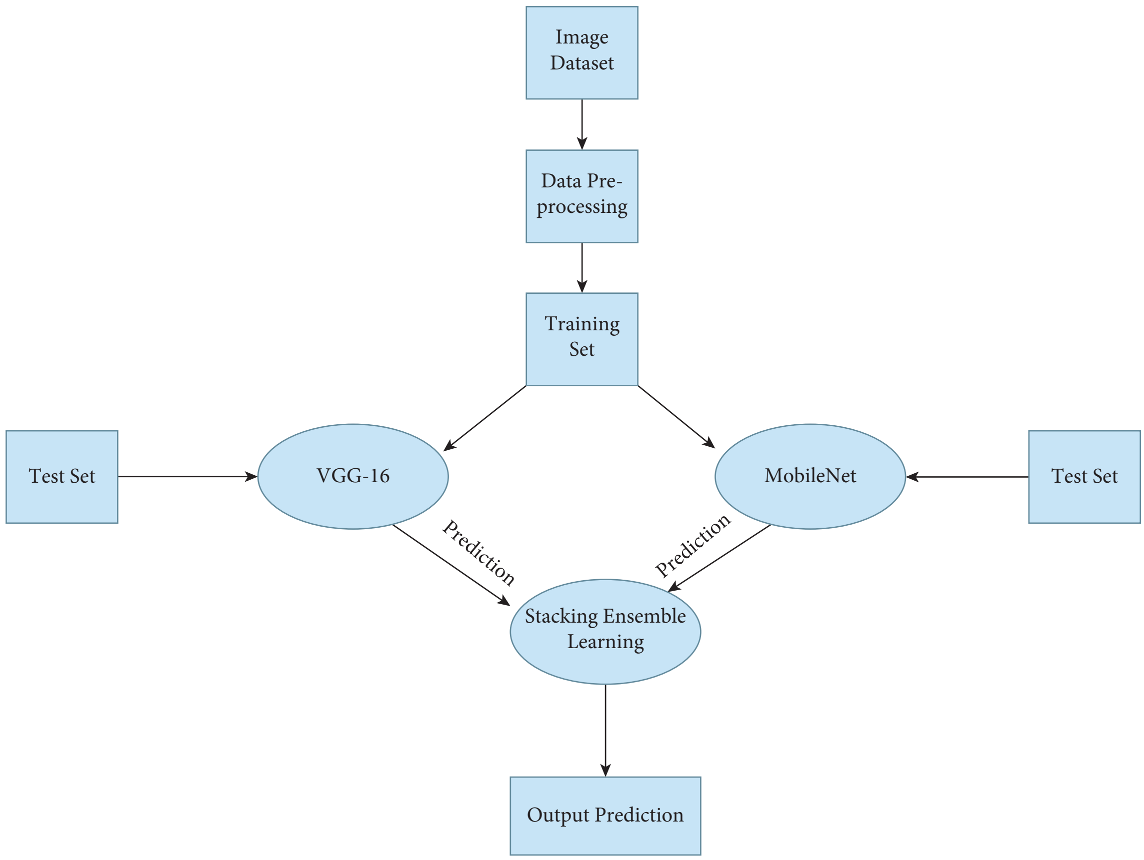

Figure 6: Proposed hybrid technique's work flow.

diseases on maize leaf that can occur and also focused on how to mitigate those diseases. With the assistance of the CIFAR10, they found nine distinct diseases and also to increase precision of the model on various epochs the model was hyper-tuned. After hyper-tuning, the model researchers obtained 98.9 percent accuracy, while with Cifar10, accuracy achieved was 98.8 percent. They demonstrate how it is possible to increase precision by increasing the number of pooling activities, and they also supplied the long-term value by consolidating brand-new calculations to increase precision or even discriminate brand-new maize diseases.

de Luna et al. [30] had taken a go from the 3 ailments of tomato leaves: *Phoma* rot, target spot, and leaf miner. They used Diamante Max's kind of tomato for examining. They produced a motor-controlled image-capturing package that catches images from every side of a leaf. They used CNN of deep learning; they compared their model with previous designs such as Fast R-CNN giving 80% accuracy and transfer learning providing 95.57% exactness and inferred that their model provided 91.67% accuracy.

Table 1 presents a summary of various crop diseases and their detection models. Thus, it is understood that the detection of crop diseases is crucial for agricultural production, quality management, and decision-making. Several projects in this field have focused on deep learning, namely, deep CNN. Although CNNs are powerful and required image processing, deep CNNs are need to be used to diagnose plant diseases [31, 32].

3. Proposed Hybrid Model for Detecting Sunflower Leaf Diseases

This work proposes a hybrid deep learning model for classifying sunflower illnesses using images, which is based on a deep learning hybrid model. Two models—VGG-16 and MobileNet—are combined, and one of the ensemble learning techniques, stacking, is used to learn the new model combination. Due to the fact that ensemble models outperform single models in terms of accuracy, the ensemble learning approach is applied in this situation. The accuracy of some existing deep learning techniques was calculated in order to select these two models. It was discovered that VGG-16 and MobileNet provide better results than the others, with 81% and 86% accuracy, respectively. Furthermore, pretrained networks are best suited for small size data sets, and because our data set is small in size, these two pretrained networks were selected for this work. The approaches of ensemble learning stacking and weighted average are used in conjunction with each other. The work flow of the proposed technique is shown in Figure 6.

Geometric transformations such as rotation, shifts, scale, zoom, and flip were accomplished via the use of image

```
start:
(1) import numpy, sklearn, tensorflow, keras as np1, sk, tf, kr
(2) def convert_img_array(img):
    If img not None:
    Return array of img
    else
    Return np1.array[]
(3) for I in imgdir://. . .imgdir contains list of images
    imgList[].append(convert_img_array(img))
    labelList[].append(i.label)//. . .i.label gives label or class of each images
(4) modify labelList with label_binarizer library
(5) image_list = np1.array(imgList, dtype = np.float16)/225.0
(6) train_test_split(image_list, labelList, 0.2,3)
(7) do Augmentation with Keras.ImageDataGenerator()
(8) Implement Models:
    from keras.applications.vgg16 import VGG16
    from keras.applications.mobilenet import MobileNet
(9) models[].append(VGG16() & MobileNet)
(10) for i in range models:
    Models[i].fit_transform();//to train the models
(11) Now combine prediction values;
    For i in range models:
    Yhat = models[i].prediction(); //stacked data set
(12) Now create stacked model
    stackedx = call process 11
    Model = LogisticRegression();
13Now to train the stacked model:
    Model.fit(stackedx, test_x);
(14) Now store prediction value of stacked model:
    Yhat = Model.predict(stackedx)
(15) Now calculate accuracy:
    Sklearn.accuracy_score(yhat, test_y)
    end;
```

Algorithm 1: Technique for detecting sunflower leaf disease.

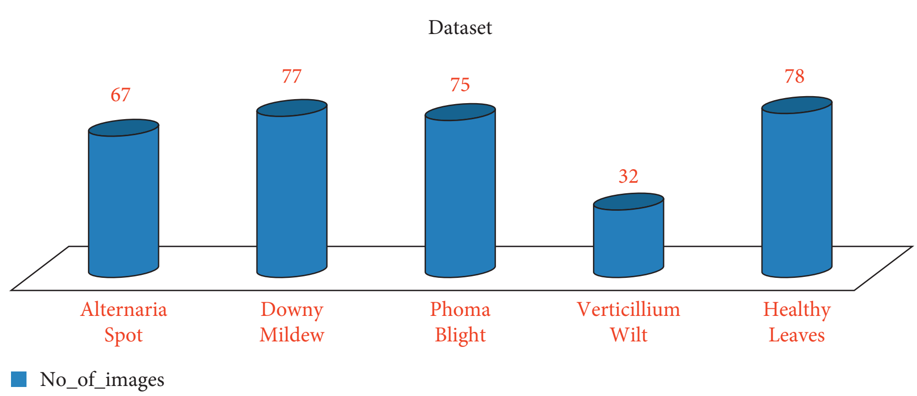

Figure 7: Data set.

augmentation in this paper. The ImageDataGenerator from Keras was used for the data augmentation process. In addition to improving the images, this strategy helps to prevent overfitting by using a batch size number that selects images for training purposes in a random manner. The algorithm for the suggested hybrid approach is detailed in the next section.

4. Results and Discussion

This section compares the proposed hybrid technique with the existing techniques on the basis of recognition or classification of sunflower leaf diseases. Data sets play an important role in classification or anything because if we do not have any data, then there is no meaning for

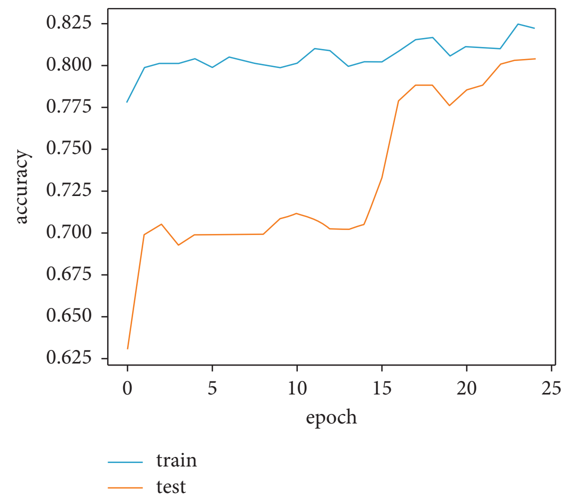

Figure 8: AlexNet.

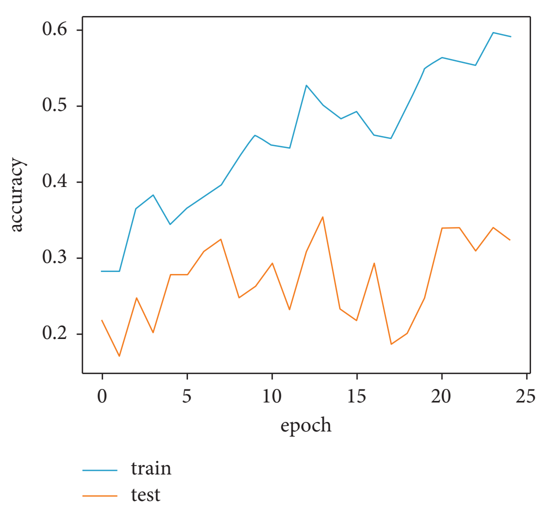

Figure 9: CNN.

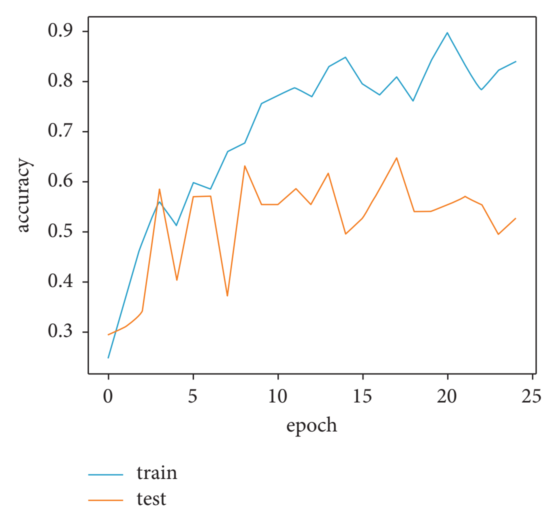

Figure 11: Inception_V3.

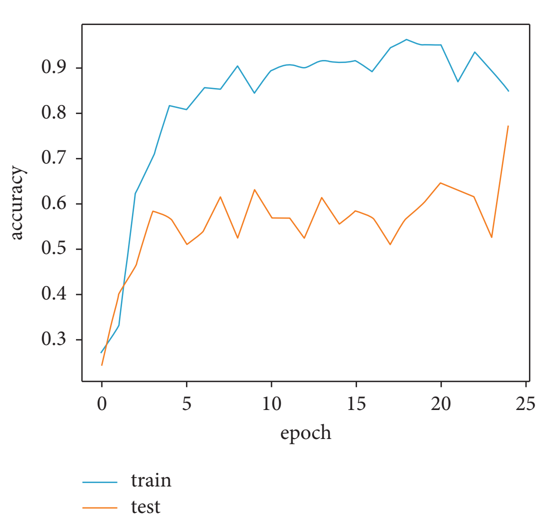

Figure 10: DenseNet-121.

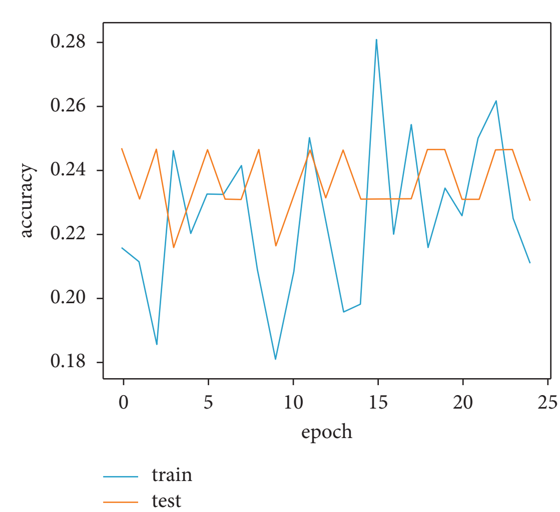

Figure 12: LeNet5.

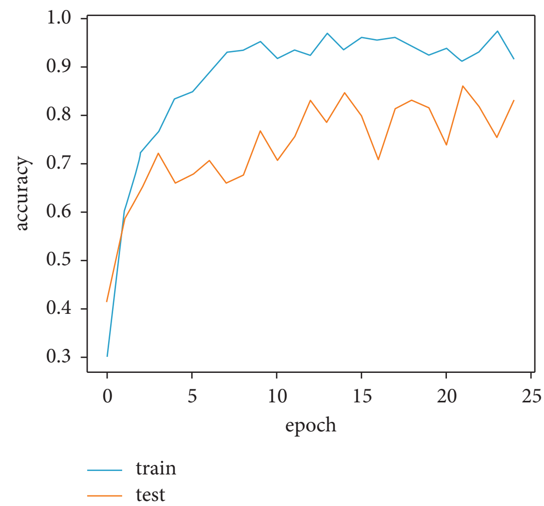

Figure 13: MobileNet.

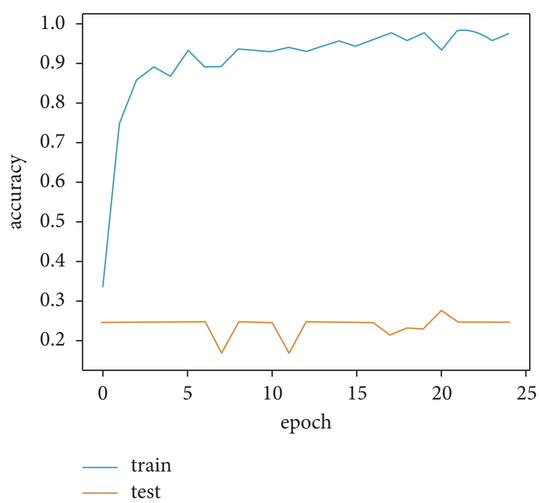

Figure 14: ResNet-50.

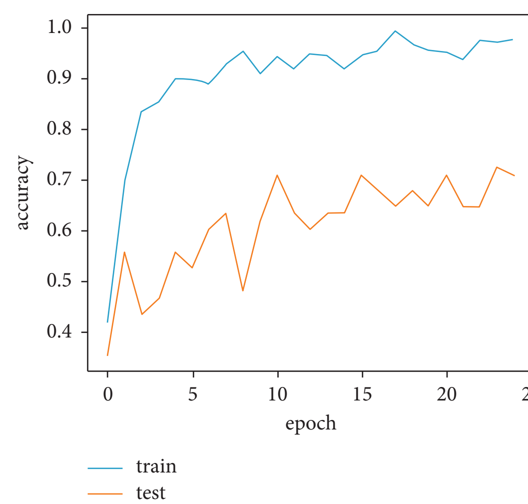

Figure 15: ResNet50V2.

calculating something or predicting something; so to achieve high accuracy in any work, we should have a proper and well-organized data set. In this work, an organized data set or the images containing diseases of sunflower is used. The data set used in this paper was taken from Google Images. In total, the data set contains 329 images including 67 images of *Alternaria* leaf spot, 78 images of healthy sunflower leaf, 77 images of downy mildew, 75 images of *Phoma* blight, and 32 images of *Verticillium* wilt. Later, the data set was split in the ratio of 80% and 20%, in which 80% images for training and 20% images for testing. In this data set, all the images are of high quality, which helps in increasing the accuracy and somehow increasing the processing speed. Figure 7 shows bifurcation of the data set used.

Initially, some existing deep learning techniques such as AlexNet, DenseNet-121, ResNet-101, ResNet-50, ResNet-50v2, Inception_v3, LeNet5, VGG-16, MobileNet, and CNNs are implemented with 7 layers. For the implementation of these techniques, the same process as of the proposed model till step 7 is used, and after that with the help of Keras library, the object of individual technique is initialized and then finally it is trained with the used data set. The accuracies of various techniques were evaluated, and Figures 8–17 show the graph between accuracy and epoch of individual model. This basically depicts that with more epoch of the model, the accuracy is increased and the model is making real predictions.

After calculating the accuracy of these models, i.e., AlexNet, CNN, DenseNet-121, Inception_V3, ResNet-50, ResNet50V2,

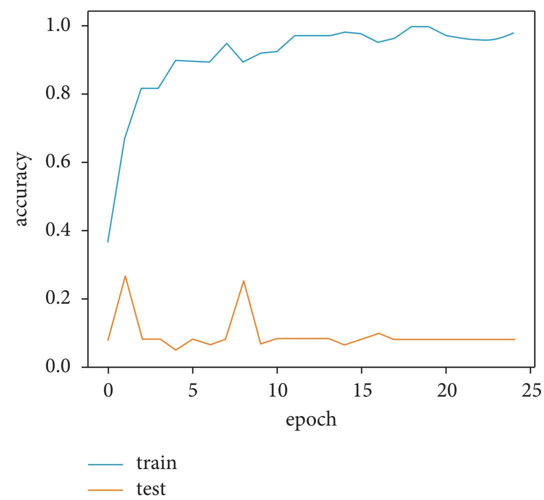

Figure 16: ResNet-101.

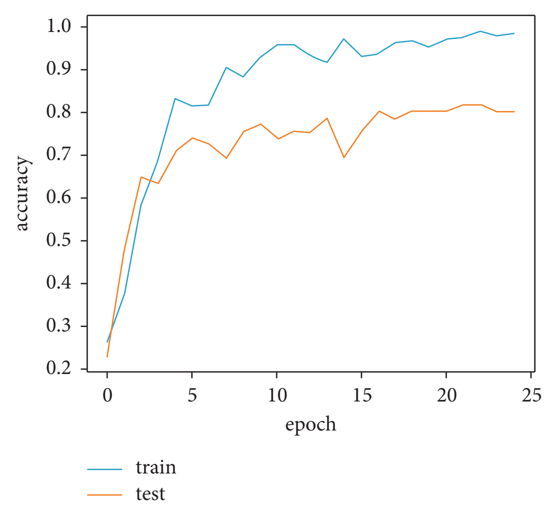

Figure 17: VGG-16.

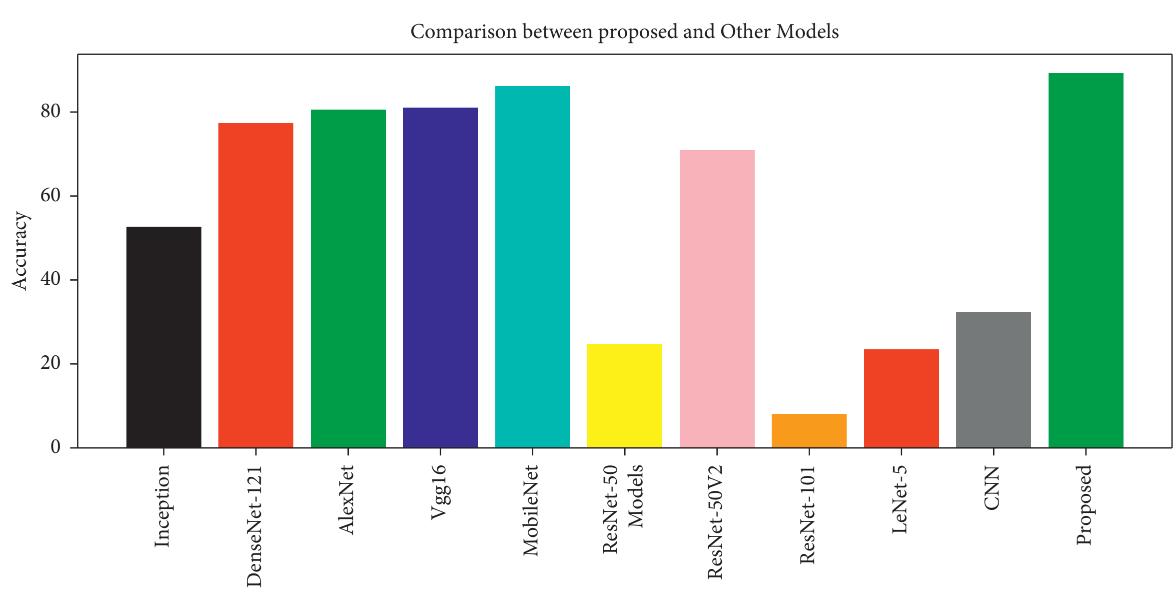

Figure 18: Comparison between the proposed and other models.

ResNet-101, and VGG-16, it can be concluded that proposed technique gives a better accuracy than the others.

5. Conclusion and Future Trends

Sunflower has several advantages, and its leaves and seeds are used in a variety of disciplines, making sunflower plants essential to our well-being as well as to the environment. The importance of detecting or recognizing infections in sunflower plants at an early stage cannot be overstated. However, this may be challenging to do manually. It is made simple by using deep learning methods or models. In this publication, a hybrid approach for the classification or identification of sunflower leaf diseases is suggested, which makes use of deep learning techniques to achieve this classification or recognition. This paper discusses four sunflower diseases, namely, *Alternaria* leaf blight, downy mildew, *Phoma* blight, and *Verticillium* wilt. *Alternaria* leaf blight is a kind of leaf blight that affects the leaves of sunflower plants. The last step is to do a comparison between the current approaches and the proposed technique. With the same data set, the proposed approach exceeds the competition, with an accuracy of 89.2%. The creation of a well-organized collection of sunflower illnesses, either by manually gathering the images of sunflowers or by utilizing a high-configuration system with many epochs, would allow for improved accuracy in the future. The graphical comparison between the proposed technique and other techniques is presented in Figure 18.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] S. O. Mezan, S. M. A. Absi, A. H. Jabbar, M. S. Roslan, and M. A. Agam, "Synthesis and characterization of enhanced silica nanoparticle (SiO_2) prepared from rice husk ash immobilized of 3-(chloropropyl) triethoxysilanea," *Materials Today: Proceedings*, vol. 42, pp. 2464–2468, 2021.

[2] S. F. Suhel, V. K. Shukla, S. Vyas, and V. P. Mishra, "Conversation to automation in banking through chatbot using artificial machine intelligence language," in *Proceedings of the 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, pp. 611–618, IEEE, Noida, India, June 2020.

[3] M. A. Jasim, M. Jamal, and AL-Tuwaijari, "Plant leaf diseases detection and classification using image processing and deep learning techniques," in *Proceedings of the 2020 International Conference on Computer Science and Software Engineering (CSASE)*, IEEE, April 2020.

[4] J. Chen, D. Zhang, and Y. A. Nanehkaran, "Identifying plant diseases using deep transfer learning and enhanced lightweight network," *Multimedia Tools and Applications*, vol. 79, pp. 1–19, 2020.

[5] G. Rastogi and R. Sushil, "Cloud computing implementation: key issues and solutions," in *Proceedings of the 2015 2nd International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 320–324, IEEE, New Delhi, India, March 2015.

[6] T. K. Lohani, M. T. Ayana, A. K. Mohammed, M. Shabaz, G. Dhiman, and V. Jagota, "A comprehensive approach of hydrological issues related to ground water using GIS in the Hindu holy city of Gaya, India," *World Journal of Engineering*, p. 6, 2021.

[7] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.

[8] J. Ma, K. Du, F. Zheng, L. Zhang, Z. Gong, and Z. Sun, "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network," *Computers and Electronics in Agriculture*, vol. 154, pp. 18–24, 2018.

[9] S. Vyas and D. Bhargava, "Big data analytics and cognitive computing in smart health systems," in *Smart Health Systems*Springer, Singapore, 2021.

[10] S. N. H. Bukhari, A. Jain, E. Haq et al., "Machine learning-based ensemble model for zika virus T-cell epitope prediction," *Journal of Healthcare Engineering*, vol. 2021, Article ID 9591670, 10 pages, 2021.

[11] Y. Zhong and M. Zhao, "Research on deep learning in apple leaf disease recognition," *Computers and Electronics in Agriculture*, vol. 168, Article ID 105146, 2020.

[12] M. Ji, L. Zhang, and Q. Wu, "Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks," *Information Processing in Agriculture*, vol. 7, no. 3, pp. 418–426, 2020.

[13] S. Uğuz and N. Uysal, "Classification of olive leaf diseases using deep convolutional neural networks," *Neural Computing & Applications*, pp. 1–17, 2020.

[14] Y. A. Nanehkaran, "Recognition of plant leaf diseases based on computer vision," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–18, 2020.

[15] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li, "Image recognition of four rice leaf diseases based on deep learning and support vector machine," *Computers and Electronics in Agriculture*, vol. 179, p. 105824, 2020.

[16] S. Ghosal and K. Sarkar, "Rice leaf diseases classification using CNN with transfer learning," in *Proceedings of the IEEE Calcutta Conference (CALCON)*, IEEE, Kolkata, India, February 2020.

[17] Howlader and M. Rasel, "Automatic recognition of Guava leaf diseases using deep convolution neural network," in *Proceedings of the 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, IEEE, February 2019.

[18] U. P. Singh, S. S. Chouhan, S. Jain, and S. Jain, "Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease," *IEEE Access*, vol. 7, pp. 43721–43729, 2019.

[19] G. Geetharamani and P. Arun, "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," *Computers & Electrical Engineering*, vol. 76, pp. 323–338, 2019.

[20] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach

based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59069–59080, 2019.

[21] A. Kumar and M. Vani, "Image based tomato leaf disease detection," in *Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, July 2019.

[22] M. Z. Hasan, "Recognition of jute diseases by leaf image classification using convolutional neural network," in *Proceedings of the 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, July 2019.

[23] M. Agarwal, "FCNN-LDA: a faster convolution neural network model for leaf disease identification on apple's leaf dataset," in *Proceedings of the 2019 12th International Conference on Information & Communication Technology and System (ICTS)*, July 2019.

[24] S. Huang, "Development and validation of a deep learning algorithm for the recognition of plant disease," in *Proceedings of the IEEE 21st International Conference on High Performance Computing and Communications; IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS)*, IEEE, August 2019.

[25] V. Singh, "Sunflower leaf diseases detection using image segmentation based on particle swarm optimization," *Artificial Intelligence in Agriculture*, vol. 3, pp. 62–68, 2019.

[26] J. Sujithra and M. F. Ukrit, "A review on crop disease identification and classification through leaf images," *European Journal of Molecular & Clinical Medicine*, pp. 1168–1183, 2020.

[27] J. F. Montecchia, M. I. Fass, I. Cerrudo et al., "On-field phenotypic evaluation of sunflower populations for broad-spectrum resistance to Verticillium leaf mottle and wilt," *Scientific Reports*, vol. 11, no. 1, pp. 11644–11714, 2021.

[28] H. Q. Cap, "A deep learning approach for on-site plant leaf detection," in *Proceedings of the 2018 IEEE 14th International Colloquium on Signal Processing & its Applications (CSPA)*, March 2018.

[29] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identification of maize leaf diseases using improved deep convolutional neural networks," *IEEE Access*, vol. 6, pp. 30370–30377, 2018.

[30] de Luna, G. Robert, E. P. Dadios, and A. A. Bandala, "Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition," in *Proceedings of the TENCON 2018-2018 IEEE Region 10 Conference*, October 2018.

[31] F. Ajaz, M. Naseem, S. Sharma, M. Shabaz, and G. Dhiman, "COVID-19: challenges and its technological solutions using IoT," *Current Medical Imaging Formerly Current Medical Imaging Reviews*, vol. 18, no. 2, pp. 113–123, 2022.

[32] Z. Yan, Y. Yu, and M. Shabaz, "Optimization research on deep learning and temporal segmentation algorithm of video shot in basketball games," *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 4674140, 10 pages, 2021.