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Deep Learning–Driven Mobile Application for Automated Mulberry Leaf Disease Detection

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Abstract—The extended research is making use of ensemble deep learning and intelligent integration for the detection of mulberry leaf diseases. While the YOLO family finds strange things rapidly, the complicated properties are found by NasNetMobile and Xception models, making the categorization more accurate. The usage of these models together in farming makes it easier and faster in finding diseases. A Flask-based frontend with user authentication allows academics and farmers to test and view disease forecasts easily in a secure and interesting manner. This larger framework would make smart agriculture more accurate, easier to use, and usable in real time.

Keywords— ***Ensemble model, deep learning, flask front end, disease detection, smart agriculture, Xception, YOLO, CNN, NasNetMobile, mulberry leaf disease.***

I. INTRODUCTION

Growing mulberries is vital for sericulture and supporting rural economies, and their leaves feed the silkworms, Bombyx mori [1]. However, mulberry trees are prone to bacterial and fungal infections that reduce the health of the leaves and consequently lower silk production [2]. Traditional methods of disease detection, relying on expertise and observations, cannot be relied upon, are very time-consuming, and not suitable for widespread monitoring [3]. There is, therefore, a need for newer and automated disease detection methods to achieve sustainable crop management and agriculture.

Convolutional Neural Networks have also more recently been doing an excellent job in picture sorting and detecting the presence of diseases in them [4]. The larger study leverages the Xception and NasNetMobile architectures to construct a complicated ensemble model that improves feature extraction and classification accuracy. Thus, integrating the YOLO framework can improve real-time detection by promptly finding the ill parts of leaves.

A Flask-based front-end application with user authentication makes it easy for academics and farmers to use the model securely for viewing projections. This new approach toward finding the leaf disease in mulberry plants is comprehensive, efficient, and user-friendly and helps in sustainable sericulture and precision agriculture [5].

II. LITERATURE SURVEY

Wang et al. applied proteomics to mulberries and silkworms to investigate changes at the protein level and molecular characteristics of plant-insect interactions. This proteomic technique explains the influence of biochemistry on silkworm development. [6]

Ghose et al. studied mulberry leaf blight for its effects on amino acids and photosynthetic pigments to understand if the disease alters leaves physiologically and biochemically. They attribute infections to leaf chemical alterations in their field pathology investigation. [7]

Zhang et al. evaluated mulberry leaf (Morus alba L.) for its impacts on metabolic diseases, integrating pharmacological data to indicate antioxidant activity and metabolic control in synthesizing therapeutic potential and delineating research gaps. Its study helps clinical and mechanistic research. [8]

Kurmi et al. built a deep CNN model using leaf pictures for the diagnosis of crop diseases to demonstrate automated disease classification. They discussed network creation, preparation of the dataset, and assessment measures. Their research suggests deep learning may help plant pathology. [9]

Shadin et al. tested many deep learning models for glaucoma identification from medical photos to show that the convolutional architectures work in ocular illness screening. Their performance analysis focuses on clinical model selection. [10]

Another work by Kurmi et al. used leaf image analysis for the classification of agricultural diseases regarding automated disease detection. The authors have discussed picture preprocessing, feature extraction, and classifier testing. Their analysis supports how the organizations should look into the models and handle datasets. [11]

Andrew et al. designed model architectures, datasets, and application scenarios for crop health monitoring by deep learning approaches to discover leaf diseases. Their review covers agricultural AI concepts and issues. [12]

Ferentinos extensively reviewed deep learning algorithms for plant disease diagnosis. He examined many CNNs and discussed deployment, augmentation, and dataset issues to ensure field reliability. The paper provides a simple model selection tool. [13]

Høye et al. suggested that deep learning and computer vision would revolutionize entomology by making species identification, behavioral studies, and even research on biodiversity possible through automatic photo analysis. Their view emphasizes how AI-assisted imagery may broaden scientific perspectives. [14]

Chen et al. proposed combining ABCK-BWTR and B-ARNet for the diagnosis of tomato-leaf diseases with a hybrid architecture that integrated deep learning with handmade or preprocessed features for better identification accuracy. Their hybrid technique has given an indication of improvements of CNN due to individualized preprocessing. [15]

Wu et al. demonstrated that generative augmentation with DCGAN may enhance classifier robustness and the balance of a dataset through the generation of synthetic pictures of tomato leaves. Their findings prove GANs benefit agricultural datasets. [16]

Chen et al. developed LBFNet, a lightweight model for diagnosing leaf diseases with a three-channel attention mechanism and pruning to realize efficient inference that can be deployed rapidly on resource-constrained devices. Accordingly, they strike a balance between accuracy and field portability. [17]

Gómez-Flores et al. employed deep neural networks along with transfer learning for the recognition of citrus greening or Huanglongbing. This approach proves the concept of automated disease screening in orchards and underlines transfer learning with limited data. Their experiment shows the industry-relevant illness monitoring [18].

Khattak et al. discussed how they go about dataset collection, network training, and performance evaluation for the deep neural network-based automated detection system to improve disease management of citrus fruit and foliage illnesses. They find out the symptoms within the leaves and fruits by applying an end-to-end approach. [19]

Masood et al. proposed a deep learning model for maize leaf diseases, namely MaizeNet, which can detect several diseases with outstanding accuracy. Architecture selection and dataset expansion were discussed. The proposed CNNs by MaizeNet are optimized for fields. [20]

Amin et al. have developed a deep learning model for maize leaf disease classification, that has a smooth pipeline from picture input to diagnosis, outperforming standard benchmarks. Their pipeline is a simple, ready-to-use design. [21]

Lv et al. used feature augmentation with a powerful version of AlexNet for the classification of maize leaf disease, but focused on preprocessing and topological modifications to reduce noise and changes. They also came up with the conclusion that even with CNNs, feature engineering is an important step. [22]

A convolutional neural network was used by Vishnoi et al. to detect the illnesses of an apple plant through its leaf photos. Experimental results and details of the design verified CNNs in domains of fruit crop diseases. Their comparison indeed proves cross-crop generalizability of deep models. [23]

Liu et al. adopted deep convolutional neural networks along with sub-class classification in order to provide more specificity in the diagnosis of apple-leaf diseases. Their work showed that hierarchical labeling may aid plant pathology. [24]

Malvade et al. compared several transfer-learning models for the classification of paddy crop stress by using pre-trained deep neural networks, highlighting their advantages for different categories of stress. Their benchmark determines the best rice crop monitoring models. [25]

Clustering-based pre-processing and object detection networks Zhou et al. performed the discovery and categorization of symptoms pertaining to rice illness using FCM-KM clustering, including Faster R-CNN fusion. The authors combine items to make the search process for stuff in some complicated settings simpler. [26]

Liu et al. proposed MixNet-CA, a Chinese rose disease detection system that uses MixNet topologies and channel attention. This enhances the multi-scale feature fusion in the discovery of subtle disease patterns. Their method provides floral disease jobs to notice. [27]

Yu et al. identified maize leaf diseases using deep learning and K-means clustering. Clustering and deep models were used for segmentation and classification. Things were easier to find in various photo settings. Their proposed hybrid pipeline reduces noise in classification. [28]

For plant leaf disease diagnosis, Geetharamani and Pandian used a medium-depth architecture for their nine-layer deep CNN. This design balanced learning capacity and processing cost and performed well on benchmark datasets. Their little network is used as a benchmark by professionals. [29]

Luo et al. improved the diagnosis of apple leaf diseases and their sub-class classification with a multi-scale feature fusion network. This framework integrates features at multiple scales, enabling better categorization and detection of lesion size. Multi-scale fusion helps in the detection of fine-grained plant disease. [30]

III. METHODOLOGY

The improved approach finds mulberry leaf disease fast and effectively using deep learning models combined with smart frameworks. A wide set of images of mulberry leaves, both sick and healthy, is collected and preprocessed by data augmentation, normalization, and scaling in order to improve the generalization of the models. The best performance is offered when Xception is combined with NasNetMobile. While NasNetMobile collects lightweight spatial hierarchies, Xception carries out disease classification based on deep separable convolutional features of images. Both of these models are independently trained for better accuracy and robustness, and then their feature representations are combined using the average ensemble technique. Real-time localization is done with the help of a family model called YOLO, which finds and highlights the sick locations on given input photos. Lastly, the frontend is a Flask web app with secure user authentication. Therefore, it allows researchers and farmers to monitor interactively the patterns of the disease, upload the leaf photos, and view the detection results. This all-in-one approach is fast, scalable, and practical for smart agricultural monitoring and disease management.

A) Proposed System

The proposed extended approach uses an ensemble deep learning architecture for the more accurate detection of mulberry leaf diseases. It combines NasNetMobile and Xception models to increase the accuracy of classification using high-level and lightweight feature extraction. The real-time detection model, YOLO, detects and locates the bad regions on the leaf photos in real time, thus helping in easy location in the field. The users will be able to upload photographs, view results, and access the sickness report through a login required front-end created with Flask. This method is ideal for smart agriculture and sericulture in terms of improving the accuracy of detection, accelerating the processing, and facilitating user access.

B) System Architecture

The main structure of the expanded model for detecting diseases in mulberry leaves has a number of stages that are coupled together in such a way that the model can precisely classify and identify diseases in real time. The first step in collecting a dataset involves taking pictures of healthy and sick leaves of mulberry plants. In order to get the input data ready for processing, photo pre-processing removes the noise, normalizes it, and scales it. A dataset is said to be more diverse with more pictures added into it, which results in preventing models from being too trained. The major architecture components include object detection and classification.

CNN, MobileNetV3-Small, ResNet50, VGG19, Xception, and NasNetMobile are involved in the training process throughout the classification. CNN, Xception, and NasNetMobile also form an ensemble model to enhance the feature extraction performance. YOLOv5x6, YOLOv8, and YOLOv9 involved in the detection phase help to accurately detect dangerous areas in photos of leaves faster. Thereafter, for ensuring their workability and reliability, the models trained will be tested against accuracy, recall, and F1-score. A full-fledged and intricate system for monitoring and controlling mulberry leaf disease combines deep learning with real-time object identification.

Fig 1. Architecture

C) MODULES

a) Data Loading:

This module requires importing a dataset of healthy and unhealthy mulberry leaf photographs.

• Other training and preparations are based on imported data.

b) Image Data Augmentation:

People use scaling, shear transformation, zooming, horizontal flipping, and reshaping to diversify datasets.

Categorizing models can avoid overfitting and make them even stronger.

c) Image Processing:

• Classes, bounding boxes, and picture blobs are created here for detection analysis.

• It reads the network layers, removes the output layers, resizes photos, and converts BGR to RGB.

d) Data Augmentation for Detection:

• To improve the dataset, we randomly rotate, flip and change viewpoint.

• The broader models can spot leaf diseases in more scenarios.

e) Model Generation:

• Ensemble Model, CNN + Xception + NasNetMobile, VGG19, MobileNetV3-Small, ResNet50 and Xception are classification models.

These are YOLOv5x6, YOLOv8, and YOLOv9, each of which is tested using the metrics Precision, Recall, and F1-Score.

f) User Signup & Login:

• This module allows the user to register and log in to a system securely.

• Verifies identities of users interacting with the application UI.

g).User Input:

• Allows uploading of mulberry leaf photo on frontend.

• Data is given to the system to predict and present ailments.

h) Prediction:

• The final outcome, sickness kind, and leaf injury are given.

• Applies the trained ensemble and YOLO model for accurate classification.

D) ALGORITHMS

a. CNN:

CNNs are neural networks that can perceive and understand visual data. In this experiment, CNN was used to differentiate whether a mulberry leaf is healthy or sick. With the incorporation of convolutional layers in this model, it can better detect diseases and find patterns.

b. MobileNetV3-Small:

It proposes the MobileNetV3-Small deep learning architecture for mobile and edge devices, which is very effective. A more compact model and efficient computation are achieved by means of depthwise separable convolutions. In this paper, mulberry leaf diseases are classified in real-time using MobileNetV3-Small. It helps us deploy it fast on cellphones without affecting accuracy.

c. ResNet50:

ResNet50 is a deep residual network that resolves the disappearing gradients problem through the use of skip connections. The project applies ResNet50 to learn complex features from pictures and to identify ailments in mulberry leaves with increased accuracy.

d. VGG19:

VGG19 is a deep and straightforward convolutional neural network that consists of 19 layers. Its strong ability in capturing hierarchical aspects makes it useful for image categorization. In this investigation, the utilization of VGG19 for detecting mulberry leaf illness proved highly effective.

e.Exception:

Xception is a sophisticated convolutional neural network that uses depthwise separable convolutions to speed up calculations. Because of its architecture, it pulls out complex details and is more accurate in classifying mulberry leaf disorders.

f. NasNetMobile:

By using neural architecture search, the lightweight design of NasNetMobile improves the speed on mobile devices. In this paper, NasNetMobile is used to find the illnesses of a mulberry leaf reliably and fast, in order to cut down on processing power required in real-time applications.

g.CNN + Xception + NasNetMobile - Ensemble Model: The ensemble model leverages CNN, Xception, and NasNetMobile for maximum utilization of the capabilities of each architecture. The combination of the model's prediction improves the categorization of mulberry leaf disease. This technique makes the model overall better, rectifying any problems with the model and thus perfect for real-time detection. h.\tYoloV5x6: The YoloV5x6 object recognition algorithm is characterized by great accuracy and real-time performance. By using YoloV5x6, this endeavor can quickly identify sick mulberry leaves. YoLoV8: New YoloV8 can find objects faster and more accurately. The project adopts YoloV8 to detect mulberry leaf diseases and provides real-time information about leaf health to farmers. j.\tYolov9: Yolov9 is the latest Yolo, and it is the best in object recognition. Its fast identification and categorization of sick mulberry leaves make Yolov9 practical for immediate action to be taken for the protection of sustainable silk production.

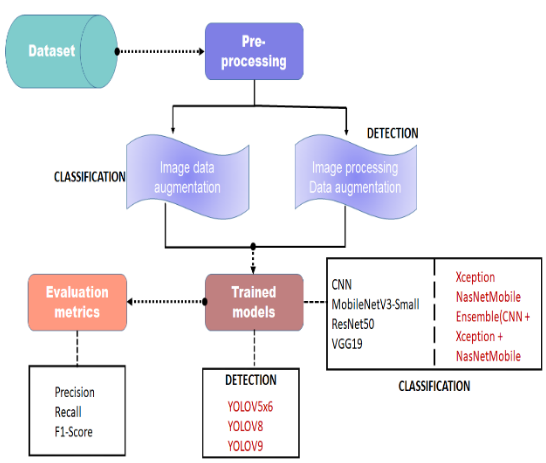

Fig 1. Architecture

A) MODULES

a) Data Loading:

- This module requires to import the dataset with healthy and unhealthy mulberry leaf photographs.
- Imported data is used for other training and preparation.

b) Image Data Augmentation:

- People utilize scaling, shear transformation, zooming, horizontal flipping, and reshaping to diversify datasets.
- Categorizing models may help us prevent overfitting and strengthen them.

c) *Image Processing:*

- Classes, bounding boxes, and picture blobs are created in this module for detection analysis.
- It reads network layers, removes output layers, resizes photos, and converts BGR to RGB.

d) Data Augmentation for Detection:

- To improve the dataset, we randomly rotate, flip, and change viewpoint.
- Broader models can identify leaf diseases in more scenarios.

e) *Model Generation:*

- Ensemble Model, CNN + Xception + NasNetMobile, VGG19, MobileNetV3-Small, ResNet50, and Xception are classification models.
- The detection models YOLOv5x6, YOLOv8, and YOLOv9 are tested using Precision, Recall, and F1-Score metrics.

f) *User Signup & Login:*

- This module allows secure system registration and login.
- Verifies users' identities before allowing access to the app's UI.

g) *User Input:*

- Allows mulberry leaf photo uploads on the front end.
- The data is provided to the system to predict and show ailments.

h) Prediction:

- The final outcome, sickness kind, and leaf injury are given.
- Uses the trained ensemble and YOLO model for accurate categorization.

B) ALGORITHMS

a. CNN:

Convolutional neural networks (CNNs) are neural networks that can detect and understand visual data. To distinguish between healthy and sick mulberry leaves, CNN is employed in this experiment. The model is able to better detect diseases and find patterns with the use of convolutional layers.

b. MobileNetV3-Small:
The mobile and edge device-specific deep learning architecture MobileNetV3-Small is quite effective. The model is smaller and easier to compute with depthwise separable convolutions. This study classifies mulberry leaf diseases in real time using MobileNetV3-Small. This helps us fast deploy it on cellphones without affecting accuracy.

c. ResNet50:
ResNet50 is a deep residual network that tackles the problem of disappearing gradients by employing skip connections. This project uses ResNet50's ability to learn complex features from pictures to increase the accuracy of classifying illnesses in mulberry leaves.

d. VGG19:
A deep and straightforward convolutional neural network, the VGG19 has 19 layers. Its usefulness for image categorization stems from its ability to accurately capture hierarchical aspects. The use of VGG19 in this investigation to detect mulberry leaf illness is highly effective.

e. Xception:
Xception uses depthwise separable convolutions to speed up calculations; it is a sophisticated convolutional neural network. The architecture of Xception makes it more accurate in classifying mulberry leaf disorders by pulling out complex details.

f. NasNetMobile:
The lightweight NasNetMobile design improves speed on mobile devices by using neural architecture search. This work uses NasNetMobile to reliably and quickly find illnesses in mulberry leaves in order to cut down on the processing power needed for real-time applications.

g. CNN + Xception + NasNetMobile - Ensemble Model:
The ensemble model uses CNN, Xception, and NasNetMobile to get the most out of each architecture. Combining the model's predictions improves the categorization of mulberry leaf disease. This method makes the model better overall and fixes any problems with it, making it perfect for real-time detection.

h. YoloV5x6:
Great accuracy and real-time performance are hallmarks of the YoloV5x6 object recognition algorithm. This endeavor can quickly identify sick mulberry leaves with the use of YoloV5x6.

i. YoloV8:
New YoloV8 can find objects quicker and more correctly. This project utilizes YoloV8 to detect mulberry leaf illnesses and provide farmers with real-time leaf health data.

j. Yolov9:
Yolov9 is the newest Yolo, and it has the best object recognition. Yolov9's quick identification and categorization of sick mulberry leaves make it feasible to take action right away to protect sustainable silk production.

III. EXPERIMENTAL RESULTS

Researchers sifted through a massive database of mulberry leaf photos to find ones with healthy leaves, rust, and spots. The generalizability of the model was enhanced by dataset enhancements and preprocessing. Ensembles of CNN, MobileNetV3-Small, ResNet50, VGG19, Xception, and NasNetMobile were trained and evaluated. The YOLOv5x6, 8, and 9 models were used for detecting tasks. The top classification accuracy was achieved by CNN + Xception + NasNetMobile, while the top real-time detection precision and recall were achieved by YOLOv9. Precision, Recall, and F1-Score all pointed to the proposed method's dependability and efficacy. Expert evaluations and Grad-CAM visualizations confirmed that the models accurately targeted diseased areas. These findings point to the expanded method as a straightforward and accurate means of diagnosing mulberry leaves in real time.
Accuracy: Determine the reliability of the test by comparing how many results are actually negative and positive. What follows is mathematics:

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Accuracy in classification or positive instances is measured by precision. Accuracy is determined by applying the following:

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

Recall: The ratio of correctly predicted positive observations to total positives demonstrates a model's ability to detect all instances of a relevant machine learning class.

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

F1-Score: An accurate machine learning model has a high F1 score. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

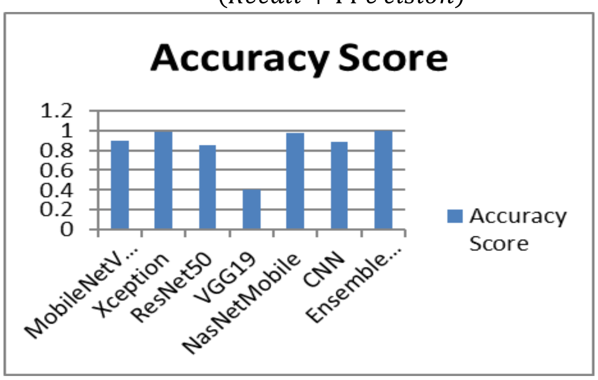

Fig 2: Accuracy graph

Model	Accuracy Score
MobileNetV3-Small	0.9
Xception	0.98
ResNet50	0.85
VGG19	0.4
NasNetMobile	0.97
CNN	0.88
Ensemble Model	0.98

Fig 3: Accuracy table

IV. CONCLUSION

The upgraded mulberry leaf disease detection system incorporates state-of-the-art deep learning with real-time detection to increase the classification accuracy and performance of the system. The model uses NasNetMobile, Xception, and a CNN-based ensemble to gather complex visual input for improved diagnosis of diseases. YOLOv5, YOLOv8, and YOLOv9 have been employed in order to enhance localization accuracy and hasten detection, which allows diseases to be discovered in real time. Users can safely and effortlessly take part in farming by using the user-friendly interface of Flask. This expanded approach is robust, scalable, and easy to understand when it comes to the early detection of diseases to assist in crop health management and the long-term production of silk.

REFERENCE

[1] E. M. Sánchez-Salcedo, P. Mena, C. García-Viguera, J. J. Martínez, and F. Hernández, ‘‘Phytochemical evaluation of white (Morus alba L.) and black (Morus nigra L.) mulberry fruits, a starting point for the assessment of their beneficial properties,’’ J. Funct. Foods, vol. 12, pp. 399–408, Jan. 2015, doi: 10.1016/j.jff.2014.12.010.

[2] M. Gundogdu, F. Muradoglu, R. I. G. Sensoy, and H. Yilmaz, ‘‘Determi nation of fruit chemical properties of Morus nigra L., Morus alba L. and Morus rubra L. by HPLC,’’ Scientia Horticulturae, vol. 132, pp. 37–41, Dec. 2011, doi: 10.1016/j.scienta.2011.09.035.

[3] S. Iqbal, U. Younas, Sirajuddin, K. W. Chan, R. A. Sarfraz, and M. K. Uddin, ‘‘Proximate composition and antioxidant potential of leaves from three varieties of mulberry (Morus sp.): A comparative study,’’ Int. J. Mol. Sci., vol. 13, no. 6, pp. 6651–6664, May 2012. [Online]. Available: https://sciprofiles.com/profile/358570?utm_source=mdpi.com&utm_medium=website&utm_campaign=avatar_name, doi: 10.3390/ijms13066651.

[4] K. Prashar, R. Talwar, and C. Kant, ‘‘CNN based on overlapping pooling methodandmulti-layered learning with SVM&KNNforAmericancotton leaf disease recognition,’’ in Proc. Int. Conf. Autom., Comput. Technol. Manage. (ICACTM), Apr. 2019, pp. 330–333.

[5] R. V. Kumar, S. Chauhan, D. Kumar, and N. More, ‘‘Nutritional composi tion in leaves of some mulberry varieties:- a comparative study,’’ in Proc. Int. Conf. Bioinf. Biomed. Technol., Apr. 2010, pp. 438–442.

[6] D. Wang, Z. Dong, Y. Zhang, K. Guo, P. Guo, P. Zhao, and Q. Xia, ''Proteomics provides insight into the interaction between mulberry and silkworm,'' J. Proteome Res., vol. 16, no. 7, pp. 2472–2480, Jun. 2017.

[7] L. Ghose, F. A. Neela, T. C. Chakravort, M. R. Ali, and M. S. Alam, ''Incidence of leaf blight disease of mulberry plant and assessment of changes in amino acids and photosynthetic pigments of infected leaf,'' Plant Pathol. J., vol. 9, no. 3, pp. 140–143, Jun. 2010.

[8] R. Zhang, Q. Zhang, S. Zhu, B. Liu, F. Liu, and Y. Xu, ''Mulberry leaf (Morus alba L.): A review of its potential influences in mechanisms of action on metabolic diseases,'' Pharmacol. Res., vol. 175, Jan. 2022, Art. no. 106029.

[9] Y. Kurmi, P. Saxena, B. S. Kirar, S. Gangwar, V. Chaurasia, and A. Goel, ''DeepCNNmodelforcrops'diseasesdetectionusingleafimages,''Multi dimensional Syst. Signal Process., vol. 33, no. 3, pp. 981–1000, Sep. 2022, doi: 10.1007/s11045-022-00820-4.

[10] N. S. Shadin, S. Sanjana, S. Chakraborty, and N. Sharmin, ''Performance analysis of glaucoma detection using deep learning models,'' in Proc. Int. Conf. Innov. Sci., Eng. Technol. (ICISET), Feb. 2022, pp. 190–195, doi: 10.1109/ICISET54810.2022.9775828.

[11] Y. Kurmi, S. Gangwar, D. Agrawal, S. Kumar, and H. S. Srivastava, ''Leaf image analysis-based crop diseases classification,'' Signal, Image Video Process., vol. 15, no. 3, pp. 589–597, Apr. 2021, doi: 10.1007/s11760-020 01780-7.

[12] J. Andrew, J. Eunice, D. E. Popescu, M. K. Chowdary, and J. Hemanth, ''Deep learning-based leaf disease detection in crops using images for agricultural applications,'' Agronomy, vol. 12, no. 10, p. 2395, Oct. 2022, doi: 10.3390/agronomy12102395.

[13] K. P. Ferentinos, ''Deep learning models for plant disease detection and diagnosis,'' Comput. Electron. Agricult., vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.

[14] T. T. Høye, J. Ärje, K. Bjerge, O. L. P. Hansen, A. Iosifidis, F. Leese, H. M. R. Mann, K. Meissner, C. Melvad, and J. Raitoharju, ''Deep learning and computer vision will transform entomology,'' Proc. Nat. Acad. Sci. USA, vol. 118, no. 2, Jan. 2021, Art. no. e2002545117, doi: 10.1073/pnas.2002545117.

[15] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, ''Identifi cation of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet,'' Comput. Electron. Agricult., vol. 178, Nov. 2020, Art. no. 105730.

[16] Q. Wu, Y. Chen, and J. Meng, ''DCGAN-based data augmenta tion for tomato leaf disease identification,'' IEEE Access, vol. 8, pp. 98716–98728, 2020, doi: 10.1109/ACCESS.2020.2997001.

[17] H.Chen,Y.Wang,P.Jiang,R.Zhang,andJ.Peng,''LBFNet:Atomatoleaf disease identification model based on three-channel attention mechanism and quantitative pruning,'' Appl. Sci., vol. 13, no. 9, p. 5589, Apr. 2023, doi: 10.3390/app13095589.

[18] W.Gómez-Flores, J. J. Garza-Saldaña, and S. E. Varela-Fuentes, ''A huanglongbingdetectionmethodfororangetreesbasedondeepneuralnetworks and transfer learning,'' IEEE Access, vol. 10, pp. 116686–116696, 2022, doi: 10.1109/ACCESS.2022.3219481.

[19] A. Khattak, M. U. Asghar, U. Batool, M. Z. Asghar, H. Ullah, M. Al-Rakhami, and A. Gumaei, ''Automatic detection of citrus fruit and leaves diseases using deep neural network model,'' IEEE Access, vol. 9, pp. 112942–112954, 2021, doi: 10.1109/ACCESS.2021.3096895.

[20] M. Masood, M. Nawaz, T. Nazir, A. Javed, R. Alkanhel, H. Elmannai, S. Dhahbi, and S. Bourouis, ''MaizeNet: A deep learning approach for effective recognition of maize plant leaf diseases,'' IEEE Access, vol. 11, pp. 52862–52876, 2023, doi: 10.1109/ACCESS.2023.3280260.

[21] H.Amin,A.Darwish,A.E.Hassanien,andM.Soliman,''End-to-enddeep learning model for corn leaf disease classification,'' IEEE Access, vol. 10, pp. 31103–31115, 2022, doi: 10.1109/ACCESS.2022.3159678.

[22] M. Lv, G. Zhou, M. He, A. Chen, W. Zhang, and Y. Hu, ''Maize leaf disease identification based on feature enhancement and DMS robust AlexNet,'' IEEE Access, vol. 8, pp. 57952–57966, 2020, doi: 10.1109/ACCESS.2020.2982443.

[23] V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan, and A. A. Khan, ''Detection of apple plant diseases using leaf images through convolu tional neural network,'' IEEE Access, vol. 11, pp. 6594–6609, 2023, doi: 10.1109/ACCESS.2022.3232917.
[24] B. Liu, Y. Zhang, D. He, and Y. Li, ''Identification of apple leaf diseases based on deep convolutional neural networks,'' Symmetry, vol. 10, no. 1, p. 11, Dec. 2017, doi: 10.3390/sym10010011.
[25] N. N. Malvade, R. Yakkundimath, G. Saunshi, M. C. Elemmi, and P. Baraki, ''Acomparativeanalysisofpaddycropbioticstressc lassification using pre-trained deep neural networks,'' Artif. Intell. Agricult., vol. 6, pp. 167–175, Jan. 2022, doi: 10.1016/j.aiia.2022.09.001.
[26] G. Zhou, W. Zhang, A. Chen, M. He, and X. Ma, ''Rapid detection of rice disease basedonFCM-KMandfasterR-CNNfusion,''IEEEAccess,vol.7, pp. 143190–143206, 2019, doi: 10.1109/ACCESS.2019.2943454.
[27] J. Liu, C. Zhang, Q. Qi, H. Li, and L. Du, ''MixNet-CA: A novel disease identification method for Chinese roses based on MixNet-s,'' IEEE Access, vol. 11, pp. 97538–97548, 2023, doi: 10.1109/ACCESS.2023.3313177.
[28] H. Yu, J. Liu, C. Chen, A. A. Heidari, Q. Zhang, H. Chen, M. Mafarja, and H. Turabieh, ''Corn leaf diseases diagnosis based on K-means clustering and deep learning,'' IEEE Access, vol. 9, pp. 143824–143835, 2021, doi: 10.1109/ACCESS.2021.3120379.
[29] G. Geetharamani and A. Pandian, ''Identification of plant leaf diseases using a nine-layer deep convolutional neural network,'' Comput. Electr. Eng., vol. 76, pp. 323–338, Jun. 2019, doi: 10.1016/j.compeleceng.2019.04.011.
[30] Y. Luo, J. Sun, J. Shen, X. Wu, L. Wang, and W. Zhu, ''Apple leaf disease recognition and sub-class categorization based on improved multi-scale feature fusion network,'' IEEE Access, vol. 9, pp. 95517–95527, 2021, doi: 10.1109/ACCESS.2021.3094802.