Tomato Classification Using Deep Learning Techniques

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Abstract: **The food industries and agriculture sectors are dependent on new technology. The Ripeness classification of tomatoes is the most important phase to maintain quality control and for the optimization of product usage. Manual sorting of tomatoes will be challenging part in food industries and agriculture sector. In this research the classification of tomato using deep learning techniques classifies the tomatoes based on their shape and color. The dataset contains 810 images segregated into 3 classes matured, half ripen and full ripen tomatoes each class contain 270 images. For the stored dataset we had applied deep learning models like SE-Net, MobileNet, DenseNet, VGG-16, ResNet and AlexNet models are performed to know which model suites well for the classification of tomatoes for the real time scenario. MobileNet and DenseNet achieved with highest accuracy. MobileNet with 98.92% of accuracy and DenseNet with 97.53% accuracy for classification of tomato.**

Key Words: *Tomato, Classification, Mobile-Net, Dense-Net*

I. Introduction

In the agricultural industry, sorting is an essential step. Sorting tomatoes according to their quality and maturity necessitates precise and effective tomato classification in order to preserve product consistency and reduce waste. In essence, conventional techniques rely on visual inspection or basic mechanical devices, which take longer and provide incorrect classification. Pre-trained models of Deep Learning techniques that enhance tomato sorting ad decrease manual labor are used to address these issues. This approach uses convolutional neural network's power to automatically classify the tomatoes into various categories by using deep learning techniques with experimental result. The goal of this clever sorting system is to improve tomato classification's accuracy and efficiency. Lowering operate costs and improving quality control in agricultural sorting system. [1] The study suggests ways to categorize tomatoes based on shape, colour and texture. It also Suggests ways to define the quality finding classification of their images. This method aims to increase tomato classification and sorting efficiency and accuracy, potentially offering an automated solution for agricultural quality control. By using image processing technique, the systems improve classification speed and accuracy, which is essential for the production and distribution of tomatoes on a large scale. [2] Through the automation and precise evaluation of characteristics like shape, colour, size, texture, Convolutional Neural Networks offer the most advanced features in tomato ripeness classification. Several convolutional layers are used to directly learn these features from images. Convolutional Neural Networks can identify subtle changes in colour, shape and size that indicate different ripening stages, making this method useful for determining tomato ripeness. [5] In agriculture, the application of Deep Learning techniques in computer vision systems can effectively enable automated, high performance tomato sorting and quality assessment, lowering manual labor costs and improving product quality. [11] To increase model robustness, especially in the face of fluctuating lighting conditions, preprocessing techniques such as scaling, data augmentation, and colour normalization are essential. Additionally, to effectively train these models and enable them to summarize and perform well across a wide range of environments, a sizable and well-annotated dataset is needed. When these models are combined with automated systems, efficiency is increased and tomato ripeness is detected. [15] Convolutional Neural Networks can reliably identify tomatoes using image data by analyzing their size, texture, colour and shape. This makes the system scalable for automated tomato cultivation management. [18].

II. Literature Survey

Researchers have experimented machine learning and deep learning for grading, classifying and evaluating quality of vegetables and fruits. Bipin et al. [1](2023) Coffee bean grading using deep learning model has been obtained with good accuracy. Bipin et al. [2] (2021) Binarization of ancient document noise reduction using deep learning technique obtained very good accuracy. Zhu [3] (2020) Vegetable classification using deep learning and machine learning compared with result of high accuracy. Jun and Jin [4] (2020) used deep learning model for vegetable detection and identification of weed, performed with good accuracy. Sachin et al. [5] (2019) vegetable classification using deep learning, encountered false positives in dense scenes, received with poor accuracy. Pandiha et al. [6] (2021) detecting the tomatoes in robotics using deep learning models for the classes distribution constraints, done with good accuracy. Ghodekar et al. [7] (2023) utilized deep learning for the classification leaf diseases in tomato for real world validation, ensured with good accuracy. Sigh et al. [8] (2022) investigated transfer learning with vegetables classifications, with limitations in dataset received with high accuracy. Rahmathunnisa et al. [9] (2020) for the detection of vegetables diseases using machine learning and clustering for classification obtained with high accuracy. Baygin [10] (2022) emphasized for fruit and vegetable classification using deep learning and machine learning, but had problem in scalability. The highest accuracy was received. Conrad and Bogomasov [11] (2021) utilise deep learning and machine learning for vegetable classification performed with high accuracy. Phan et al. [12] (2023) the classification of tomatoes using deep learning techniques, focused on computation and memory limitations. Chen [13] (2024) the vegetable classification using deep learning, with the limited dataset obtained good accuracy. Vijaykanthan et al. [14] (2021) classification of vegetables applied transfer learning. The obtained accuracy was high. Tripathi and Maktedar [15] (2021) classification for feature extraction in multiple object images. The accuracy received average. Ahmed et al. [16] {2021) vegetable classification using transfer learning obtained with high accuracy. El-Ghoul et al. [17] (2024) vegetable classification using deep learning for public datasets, overcomes with issues of mixed object classification, achieved with high accuracy. Sarkar et al. [18] (2022) used deep learning for vegetable dataset but encountered with background challenge issues received with good accuracy. Yuseheng et al. [19] (2021) classification using deep learning models, achieved with high accuracy. Turaev [20] (2021) used transfer learning for appearance and not considering internal defects received with high accuracy. Monu Bhagat [21] (2020) leaf disease classification in bell pepper using deep learning and machine learning received with good accuracy. T. Swathi et al. [22] (2023) The classification and prediction of crop for the soil using machine learning achieved with high accuracy. Sukanya S et al. [23] (2022) fruits leaf diseases for Fungai using deep neural network got good accuracy. Wasyihum Sem Admass et al.[24] (2023) early disease detection in mango using CNN obtained with good accuracy. Ancy Stephen et at.[25] (2023) classifying and identifying the cotton plant health using deep learning received with high accuracy. Upandhyay et al. [26] (2021) disease on rice using deep learning models for rice plant received with good accuracy.

III. PROPOSED METHOD

In order to assess the effectiveness the six CNN models like DenseNet, MobileNet, VGG16, AlexNet, ResNet and SE-Net are used to categorize the tomatoes according to their level of ripeness we conducted this study. The best option for real-time agricultural applications is provided by MobileNet and DenseNet.

A. Densenet

The distinctive densely connected layers of DenseNet's architecture make it highly effective for tomato classification. By connecting each layer to the next, DenseNet makes sure that features learned by older layers are passed straight to subsequent layers, improving feature reuse and propagation. This indicates that compared to conventional CNNs, the model is more effective at identifying fine details and patterns in tomato photos. The tomato ripening stages can therefore provide the highest accuracy. The difference between fully ripened, half-ripened, and matured tomatoes are easily recognized by DenseNet due to its wide range of connections. DenseNet is able to provide accurate and dependable classification by utilizing these sophisticated features. With the help of this technology, farmers can increase crop quality and decrease manual labor while receiving precise information about the best time to harvest their crops.

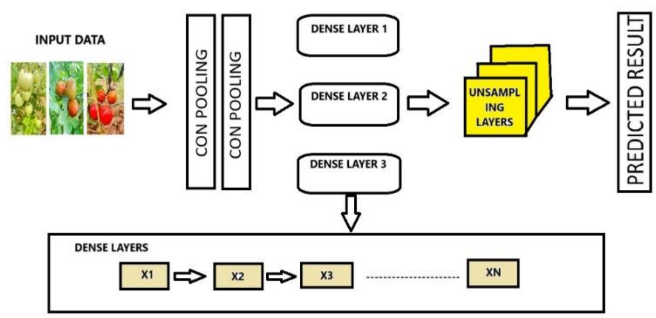

Fig 1: Dense Net Architecture

B. Mobilenet

Because of its speed and efficiency, MobileNet is a great option for real-time applications and agricultural industry. For image classification tasks, this approach is useful. Because it employs depthwise separable convolution layers, it maintains high accuracy while lowering computational risks. With the help of this features, MobileNet can quickly and precisely determine the different stages of tomato ripeness based on the tomato's size, shape, color, and texture. The lightweight design of MobileNet makes it possible to deploy on mobile and edge devices while guaranteeing usability and accessibility in agricultural settings.

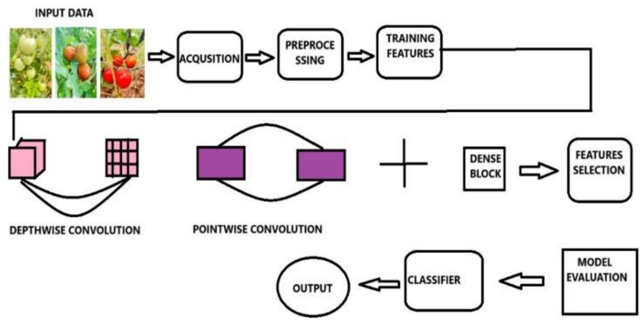

Fig 2: Mobile Net Architecture

C. *VGG16*

Because of 16 layers, VGG16 is known for its straightforward and reliable architecture. Throughout the network, it applies little 3*3 filters. It involves many factors and is computationally intensive.

D. *AlexNet*

Won the 2012 ImageNet competition and represented a breakthrough in deep learning. It consists of eight layers. To avoid overfitting, it uses ReLU activations and invented the dropout concept.

E. ResNet (Residual Network)

Skip connections were included to help with gradient flow during training. This design prevented vanishing gradient issues and enabled the training of extraordinarily deep networks.

F. *SE-NET (Squeeze-and-Excitation Network);*

Excitation blocks in SE-Net(Squeeze-and-Excitation Network) mimic channel interdependencies to modify feature responses. By emphasizing important features, this outperforms conventional convolutional networks.

In real-time and resource constrained applications, MobileNet and DenseNet perform better in terms of efficiency, accuracy, and usability than other models such as VGG16, SE-NET, AlexNet, and ResNet. They are ideal for tasks like tomato ripeness classification because of their novel structures, which allow for high performance with little processing resources.

IV. METHODOLOGY

We have taken 810 tomato photos from the farm to guarantee precise tomato classification. Normalization and data augmentation were used to preprocess the dataset in order to increase diversity and decrease overfitting, which improved image quality and accuracy.

A. *Data Collection*

Images of tomatoes are taken during the growing season from tomato farms. The 810 photos in our dataset are further divided into three classes such as Mature, Half-Ripen, Full-Ripen. Each class has 270 photos. By doing this, a variety of tomato ripeness conditions are represented.

Table1: Dataset Collection

Attributes	Description
Dataset Name	Tomato Classification Dataset
Classes	3 classes namely Matured, Halif ripen, Full ripen
Number of Images	810
Image Size	224*224 pixels
Source	Tomato Farm
Collection Method	Images are classified based on their shape and colour
Device Name	iPhone 14 Plus
iOS Version	18.1
Model Number	MQ503HN/A

Fig3: Sample images of Datasets (1. Matured, 2. Half-Ripen, 3. Full-Ripen)

B. *Data Preprocessing*

During the data preprocessing step, images are normalized by rescaling pixel values to the range [0,1] in order to facilitate effective learning. Data augmentation methods that decrease overfitting and increase dataset diversity include 20-degree rotations and horizontal flipping. To ensure that the model is trained on one subset and validated on another to enhance performance and prevent overfitting, the dataset is split into two sections 80% for training and 20% for validation.

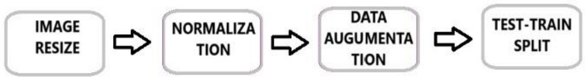

Fig 4. Data Preprocessing

The data preprocessing workflow for tomato classification is depicted in Figure 4. The pixel value was standardized to [0,1] for quick learning, the image was rescaled for uniform size, and improved methods like flipping and rotation were used to expand the range. In order to facilitate model training and testing, the datasets are separated into training and testing categories.

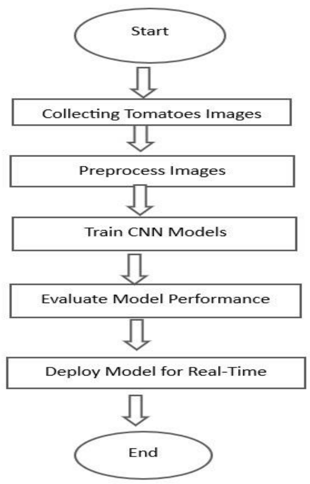

Fig 4: Flow chart of Tomato classification

Figure 4 illustrates the tomato classification flow chart. In the first step, tomato photos are gathered from the farm and categorized into three groups namely full-ripen, half-ripen, and matured. The following steps involves preprocessing the images, such as rescaling, normalization and then using MobileNet and DenseNet to train the images. Additionally, a loss graph and accuracy graph are produced, which show how well the model predicts ripeness categories.

V. EXPERMENTAL RESULT

The accuracy, loss, precision, recall and F1-score were used to assess the tomato classification based on MobileNet and DenseNet. Both models had the best accuracy and least loss. The accuracy and loss graph demonstrates that the model offers dependable and effective classification.

Table 2: Evaluation Metrics

Metrics	Mobile Net	Dense Net
Accuracy	98.92%	97.53%
Loss	0.0152	0.0774
Precision	0.0563	0.3165
Recall	0.358	0.3179
F1- Score	0.3528	0.2629

In terms of accuracy and loss, MobileNet performs better than DenseNet, as indicated by the evaluation metrics listed in Table 2. MobileNet surpasses DenseNet at 92.72% and achieves maximum accuracy of 96.92 with a batch size of 16. Additionally, MobileNet exhibits better convergence during training, as evidence by its significantly lower loss (0.0152) compared to DenseNet's 0.0389. Although DenseNet outperforms MobileNet in terms of F1score, precision and recall, its lower loss and higher accuracy indicate that it is more appropriate for applications that place a higher value on performance metrics like accuracy. Together they provide a performance-efficiency balance for precise tomato classification.

A. *Accuracy and loss graph analysis:*

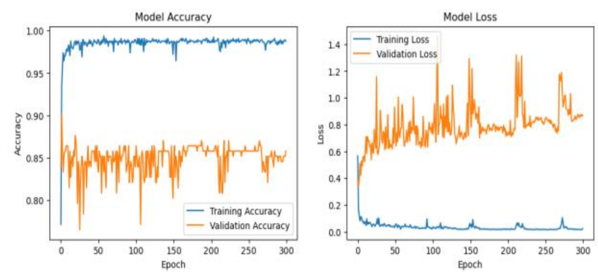

Fig 5: Accuracy and Loss Graph of DenseNet

The trained and validation performance of the DenseNet model over 300 epochs is shown in Fig 5. The model performs well with the training data, as evidenced by the training accuracy blue line staying high and the training loss being continuously low however, the validation loss is unstable and does not decrease steadily, while the validation accuracy orange line fluctuates and stays lower

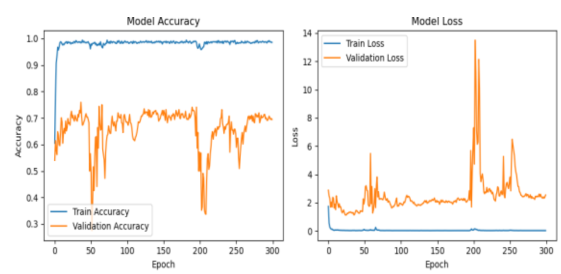

Fig 6 Accuracy and Loss Graph of MobileNet

The MobileNet model's performance is shown in Fig 6. The blue line for training accuracy indicates that performance on the training data is good since accuracy is consistently high and training loss is low. The validation accuracy orange line, on the other hand, indicates that while validation loss is highly variable with spikes, validation accuracy occasionally swings and dips significantly.

It is evident that MobileNet and DenseNet are the best options after examining the accuracy and loss graphs of various models. Across a range of epochs and batch sizes, both models continuously showed excellent accuracy and minimal loss.

Because of their effectiveness and strong feature extraction capabilities, MobileNet and DenseNet are perfect for enhancing crop quality and supporting accurate harvesting decisions. This combination improves the classification process's overall effectiveness.

Table 3: Comparison table of MobileNet and DenseNet with different batches and epochs

#MOBILEN	batch	epoch	accuracy	loss	epoch	accuracy	loss	epoch	accuracy	loss
80,20	16	100	98.46	3.16	200	0.9892	0.0167	300	0.9892	0.0152
	32	100	98.77	1.81	200	0.9861	0.0389	300	0.9877	0.0263
	64	100	97.84	4.99	200	0.9877	0.016	300	0.9877	0.0253
60,40	16	100	96.3	11.33	200	0.9774	0.068	300	0.9272	0.0389
	32	100	97.74	3.72	200	0.9856	0.0255	300	0.9753	0.774
	64	100	98.15	2.59	200	0.9877	0.02	300	0.9856	0.0196
70,30	16	100	98.24	3.17	200	0.9859	0.0297	300	0.9877	0.0181
	32	100	98.24	2.66	200	0.9894	0.0194	300	0.9877	0.0168
	64	100	98.24	2.81	200	0.7988	0.0283	300	0.9877	0.0172
#DENSENE	batches	epochs	accuary	loss	epochs	accuracy	loss	epoch	accuracy	loss
80,20	16	100	95.93	0.1652	200	0.9556	0.2112	300	0.9642	0.1862
	32	100	97.04	0.1244	200	0.9568	0.1632	300	0.9667	0.1458
	64	100	96.67	0.141	200	0.9667	0.1559	300	0.9642	0.1574
70,30	16	100	0.9519	0.2093	200	0.958	0.1535	300	0.9605	0.1602
	32	100	0.9531	0.1507	200	94.07	0.2429	300	0.9296	0.2996
	64	100	0.963	0.1353	200	95.06	0.228	300	0.9345	0.0345
60,40	16	100	0.9309	0.2869	200	0.9837	0.35	300	0.9099	0.4865
	32	100	0.9099	0.4184	200	0.9395	0.1842	300	0.9222	0.3807
	64	100	0.9395	0.2146	200	0.9407	0.1959	300	0.9407	0.1886

Six models like RESNET, MOBILENET, ALEXNET, SE-NET,DENSENET AND VGG16 are compared in Table 3. As can be seen in the above table, MobileNet and DenseNet performed better than the others. The models MobileNet and DenseNet work well for classifying tomatoes in this study because MobileNet continuously achieved the highest accuracy across a range of epochs and batch sizes.

CONCLUSION AND FUTURE SCOPE

This advanced system uses deep learning techniques to classify tomatoes according to their level of ripeness. DenseNet and MobileNet both achieved the highest accuracy of 97.53%, while MobileNet received 98.92%. For several batches and epochs, the accuracy was higher than 95%. Sorting tomatoes according to their colour and shape was made more accurate and efficient by these models

Through quality control of the tomatoes and consistent results free from human error , this project helps farmers make decision about tomato harvesting in a field. Large datasets may be used in subsequent research to increase the model's efficiency and accuracy, which would allow for real-time classification on edge devices. Using sensors from the Internet of Things, which are useful in the agricultural sector, would improve the accuracy and efficiency of classification.

REFERENCES

1. BJ, B. N., KM, A. N., Shalwin, A. S., & Raghavendra, V. (2023, August). Coffee Bean Grading Based on Weight Estimation Using Densenet121 Model. In *2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA)* (pp. 1-6). IEEE. **DOI:** 10.1109/ICCUBEA58933.2023.10392243

2. BJ, B. N., & Nair, A. S. (2021, April). Ancient horoscopic palm leaf binarization using A deep binarization model-RESNET. In *2021 5th International Conference on Computing*

Methodologies and Communication (ICCMC) (pp. 1524-1529). IEEE. **DOI:** 10.1109/ICCMC51019.2021.9418461
3. Zhu, L. (2020). High performance vegetable classification from images based in AlexNet deep learning model. *IEEE Access*. DOI: 10.25165/j.ijabe.20181104.2690
4. Jun, X., & Jin, J. (2020). Weed identification using deep learning and image processing in vegetable plantation. *Agricultural Informatics*. **DOI:** 10.1109/ACCESS.2021.3050296
5. Sachin, C., Manasa, N., Sharma, V., & Kumar, N. K. (2019). Vegetable classification using YOLO algorithm. *Pattern Recognition and Image Analysis*. **DOI:** 10.1109/ICon-CuTE47290.2019.8991457
6. Padilha, T. C., Moreira, G., Magalhães, S. A., Santos, F. N., Cunha, M., & Oliveira, M. (2021). Tomato detection using deep learning for robotics application. *Robotics and Automation*. doi.org/10.1007/978-3-030-86230-5_3
7. Ghodekar, A. R., Sultanova, N., Jayabalan, M., & Mustafina, J. (2023). Tomato plant leaf disease classification using deep learning. *Plant Pathology Journal*. **DOI:** 10.1109/DeSE60595.2023.10469522
8. Singh, H., Singh, R., Goel, P., Singh, A., & Sharma, N. (2022). Automatic framework for vegetable classification using transfer-learning. *Machine Learning in Agriculture*. **DOI:** https://doi.org/10.37391/IJEER.100257
9. Rahmathunnisa, U., Nallakaruppan, M. K., & Kumar, S. K. (2020). Vegetable disease detection using K-means clustering and SVM. *Computers and Electronics in Agriculture*. **DOI:** 10.1109/ICACCS48705.2020.9074434
10. Baygin, M. (2022). Vegetable and fruit image classification with SqueezeNet-based deep feature generator. *Computational Intelligence*. https://doi.org/10.55525/tjst.1071338
11. Conrad, S., & Bogomasov, K. (2021). Efficient fruit and vegetable classification and counting for retail applications using deep learning. *International Journal of Retailing*. https://doi.org/10.1145/3505711.3505720
12. Phan, Q. H., Nguyen, V. T., Lien, C. H., Duong, T. P., Hou, M. T., & Le, N. B. (2023). Classification of tomato fruit using YOLOv5 and CNN models. *Agricultural Engineering International*. ;**https://doi.org/10.3390/plants12040790**
13. Chen, H. (2024). Application of machine learning in vegetable classification and recognition. *Journal of Artificial Intelligence Research*. https://doi.org/10.54097/n2zv5694
14. Vijayakanthan, G., Kokul, T., & Pakeerathan, S. (2021). Classification of vegetable plant pests using deep transfer learning. *Journal of Plant Protection*. **DOI:** 10.1109/ICIAfS52090.2021.9606176
15. Tripathi, M. K., & Maktedar, D. D. (2021). Detection of various categories of fruits and vegetables through descriptors using machine learning techniques. *Pattern Recognition Letters*. https://doi.org/10.1504/IJCISTUDIES.2021.113819
16. Ahmed, M. I., Mamun, S. M., & Asif, A. U. (2021). DCNN-based vegetable image classification using transfer learning: A comparative study. *Journal of Image Processing and Pattern Recognition*. **DOI:** 10.1109/ICCCSP52374.2021.9465499
17. El-Ghoul, M., & Abu-Naser, S. S. (2024). Vegetable classification using deep learning. *Journal of Agricultural Informatics*. DOI: 10.1016/j.ijcse.2024.06.003.
18. Sarkar, P., Sarkar, P., Saha, D., & Maiti, A. (2022). Indian vegetable image classification using convolutional neural network. *Computers in Agriculture and Food Processing*. https://doi.org/10.36375/prepare_u.foset.a301
19. Yuesheng, F., Jian, S., Fuxiang, X., Yang, B., Xiang, Z., & Shengqiao, X. (2021). Circular fruit and vegetable classification based on optimized GoogLeNet. *International Journal of Computer Vision*. **DOI:** 10.1109/ACCESS.2021.3105112
20. Turaev, S. (2021). Application of transfer learning for fruits and vegetable quality assessment. *Journal of Quality and Reliability Engineering*. DOI: 10.1109/IIT50501.2020.9299048
21. Bhagat, M., Kumar, D., & Kumar, S. (2023). Bell pepper leaf disease classification with LBP and VGG-16 based fused features and RF classifier. *International Journal of Information Technology, 15*(1), 465–475. https://doi.org/10.1007/s41870-022-01136-z
22. Swathi, T., & Sudha, S. (2023). Crop classification and prediction based on soil nutrition using machine learning methods. *International Journal of Information Technology, 15*(6), 2951–2960. https://doi.org/10.1007/s41870-023-01345-0
23. Gaikwad, S. S., Rumma, S. S., & Hangarge, M. (2022). Fungi affected fruit leaf disease classification using deep CNN architecture. *International Journal of Information Technology, 14*(7), 3815–3824. https://doi.org/10.1007/s41870-022-00860-w
24. Admass, W. S., Munaye, Y. Y., & Bogale, G. A. (2024). Convolutional neural networks and histogram-oriented gradients: A hybrid approach for automatic mango disease detection and classification. *International Journal of Information Technology, 16*(2), 817–829. https://doi.org/10.1007/s41870-023-01605-z
25. Stephen, A., Arumugam, P., & Arumugam, C. (2024). An efficient deep learning with a big data-based cotton plant monitoring system. *International Journal of Information Technology, 16*(1), 145–151. https://doi.org/10.1007/s41870-023-01536-9
26. Upadhyay, S. K., & Kumar, A. (2022). A novel approach for rice plant diseases classification with deep convolutional neural network. *International Journal of Information Technology, 14*(1), 185–199. https://doi.org/10.1007/s41870-021-00817-5