Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7657969

A NOVEL APPROACH TO POMEGRANATE LEAF DISEASE DETECTION USING DEEP LEARNING ALGORITHMS

Nirmal Mahesh Dattatray[1], Dr. Pramod Pandurang Jadhav[1] and Dr. Santosh Pawar[2]
[1]Department of Computer Science & Engineering, Dr. A.P.J. Abdul Kalam University,
Indore (M.P.) 452010, India
[2]Department of Electronics & Communication Engineering, Dr. A.P.J. Abdul Kalam University,
Indore (M.P.) 452010, India
Corresponding Author Email : vedic1234@gmail.com

Abstract The major purpose of this study is to evaluate whether a Deep Learning (DL) model can perform better in image processing when it comes to identifying the presence of a disease in a pomegranate leaf.For this, a collection of 559 images from the Mendeley databases is gathered. There are images of both healthy and sick pomegranate leaves in this collection. Out of these, 540 images are chosen for testing, training, and validation of the DL models. However, the aforementioned operations can't start until the image has undergone preprocessing. The correct operation of the DL models is ensured by this preprocessing. Image resizing, image rescaling, and data augmentation are all included in the preprocessing.The steps of image resizing and rescaling make sure that the images are uniform in terms of size, dimensions, and pixel count. The data augmentation phase increases the training dataset's image count. This procedure extends the training period and ostensibly improves DL model performance. After preprocessing, the images are employed to train the built-in DL models. Three algorithms are used in the modeling process. The algorithms are Convolutional Neural Network (CNN), Convolutional Neural Network -Support Vector Machine (CNN-SVM), and Convolutional Neural Network-Long Short-Term Memory network(CNN-LSTM). All three models use the same number of images for training and validation. The models are evaluated for the final metrics after training and validation.Accuracy, True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), and False Negative Rate (FNR) are some of the measures that were used in this study. Based on test results, a confusion matrix was also created. The CNN-LSTM algorithm is ultimately discovered to be able to offer a superior accuracy value than the other two methods. One final time, a real-time image is used to assess the model's performance. This study will likely be modified in the future to include the capability of both predicting and identifying the type of disease. Additionally, real-world images rather than those downloaded from the internet are anticipated to be utilized in place of the dataset used in this study to improve prediction accuracy.

Keywords: Disease detection, deep learning models, image preprocessing, confusion matrix, etc.

1. Introduction

Researchers state that farmers and agriculturists must spot the presence of plant disease in its early stage to properly treat the plants (Sardoganet al., 2018). They address the use of a CNN model and the Learning Vector Quantization (LVQ) technique for the detection and categorization of disease on tomato leaves. The dataset consists of 500 images of tomato leaves with four different disease signs. They have modeled a CNN for automatic feature extraction (FE) and classification. Observations of leaf colors are commonly employed in scientific investigations of plant diseases. This method employs three channels derived from the RGB components and applies filters to each of those. The network was trained by feeding the feature vector produced by the convolutional layer into the LVQ. The experimental results show that the proposed technique is useful for detecting four distinct diseases that affect tomato leaves. An enhanced Yolov4 algorithm was employed in research to automatically detect and identify three diseases that affect sunflower leaves (Chen et al., 2021). To improve the Yolov4 network model's central box for detecting niche lesions on leaves, first need to construct the three MobileNet model functions, construct three effective feature layers for each MobileNet model, and then utilize these layers in place of the original model's optimized feature layer.

Misdiagnosis can result in chemical overuse that costs money, environmental imbalance and contamination, and the establishment of pathogen strains that are resistant to treatment (Sriniti et al., 2021). The process of diagnosing diseases nowadays is time-consuming, expensive, and dependent on human scouting. Image acquisition, processing, and segmentation are the primary stages in the automatic identification of plant diseases. These are proceeded by augmentation, FE, and classification by AI framework. In this investigation, researchers employed several distinct algorithms to successfully recognize four apple diseases from leaf images. The study produced an accuracy higher than 99%. Since edge detection must be performed in real-time, quick processing times are needed(Yusoff, NorfarahinMohdet al., 2018). This work suggests a hardware implementation for a legitimate edge detection algorithm for detecting Hevea leaf illnesses (rubber tree leaves) in images. In this study, images from three prominent Hevea leaf diseaseswere compared. The Sobel edge detection technique could recognize the disease on leaves. This technique created with MATLAB was examined for the real-time edge detection outcome created by FPGA Cyclone IV E and presented on a screen.A study suggested a framework with four components (Prakash et al., 2019). Image preprocessing comes first, then leaf segmentation using K-means clustering to detect the sick spots. The classification of disorders is the second phase, followed by FE. Statistical GLCM characteristics are used to extract texture features, and SVM is used to classify the data (SVM).

The majority of illnesses in cotton plants often manifest on the leaves, flowers, and fruits (Bodhe et al., 2018). The suggested research aims to recognize and classify illnesses affecting cotton leaves. The project entails the creation of an Android mobile application sample using a pattern communicative approach. The different cotton farms in the Vidharbha region are where the images for the android application were taken. Farmers may quickly spot diseases affecting the cotton crop by using internet-connected smartphones. The suggested approach recognizes illness tendencies in their earliest stages.A diagnosis approach targeting banana leaf diseases that utilizes image processing is suggested since the banana diseases had a direct impact on banana quality and yield (Jianquing et al., 2022). First, from the original smartphone-collected photograph of banana leaf disease, the green backdrop, also including healthy leaves and weeds, is removed using the color segmentation method. In addition, the segmented image is converted to a YUV color space. Employing standard image samples, the following color features like variance, mean, and skewnesses of the R, G, B, Y, U, and V elements in the disease regions, are gathered and processed to generate feature vectors on every banana leaf disease. The least Euclidean distance algorithm is employed to detect banana leaf disease.A crucial necessity in a developing agricultural economy such as India is early plant leaf detection (Ashok et al., 2020). Leaf diseases must be detected at an extremely early stage, and predictive approaches must be adopted, for plants to be made safe and for the agricultural sector to avoid costs.This is true not just because our economy is based on agriculture but also because we need to feed a sizeable contingent. To create a trustworthy, safe, and precise solution for detecting leaf disease, this study suggests applying image processing approaches based on clustering, segmentation, and open-source methods. The system would be used to analyze images of tomato leaves.

The identification and detection of leaf diseases have received an increasing amount of research and attention since the creation and widespread adoption of intelligent agricultural systems (Li et al., 2020The study of apple leaf diseases required the use of both healthy and diseased leaf datasets to investigate detection and classification. As a means of evaluation and improvement, we used ResNet, SVM, and VGG-CNN models for disease segmentation. On the last test, ResNet-18, which had fewer ResNet layers, had better recognition effects.In actuality, finding leaf diseases is done manually by professionals, which takes extra time for subsequent management measures (Padol et al., 2016). The right control measures cannot be implemented at the right time without an accurate disease diagnosis. This study aims to introduce a novel way for recognizing the infections that harm grape leaves, to reduce loss and increase accuracy through automation. Classification is accomplished independently using Support Vector Machine (SVM) and Artificial Neural Network (ANN). The fusion categorization method is introduced as a novel classifier for disease detection in grape leaves, bringing together SVM and ANN.

Knowledge of operational equivalence and the collaborating elements at the fundamental level is necessary for the accurate diagnosis of plant leaf diseases (Sunitha et al., 2022). To effectively control plant diseases, DL helps in their detection and provides initial as well as more prompt diagnosis. An individual infusion is transmitted, allowing for standardized automated disease diagnosis. A CNN is developed for plant leaf spot detection. The proposed model's average classification accuracy is found to be greater than ninety percent. To conduct a comparative analysis, The suggested CNN algorithm has been investigatedas an example of the multi-layer perceptron neural classification algorithm.Even though many of the current methods have produced better outcomes, obstacles still stand in the way of optimizing the plant leaf disease detection procedure (Metre et al., 2022). This study examines numerous methods in the areas of image processing, Machine Learning (ML), DL, and swarm intelligence to identify plant leaf diseases. This study offers a thorough taxonomy of the numerous plant diseases in addition to a dataset that would have been often used in earlier studies to train and test strategies for identifying plant leaf diseases and classifying them. It is essential to comprehend the numerous illnesses that might affect plant leaves to treat them.A system identifies the disease that infected the leaf, as well as the affected portion of the leaf (Indhumadhi et al., 2019). Image processing is used to accomplish this; systems exist that foretell leaf illnesses. K-Medoid clustering and Random Forest techniques are used by the system to increase the accuracy of leaf disease diagnosis. The afflicted area of the blade is first located using pre-processing, followed by the classification algorithm is used. Then, 13 characters are extracted, including Variance, Smoothness, Contrast, Correlation, Energy, Kurtosis, and Skewness. These 13 characters will be used to assess the accuracy of the data and identify any diseases.

A new technique that helps boost the quality and output of the nation's agricultural sector, particularly tomato production, is the use of smart farming systems in conjunction with the required infrastructure (De Luna et al., 2019) This work created the ground-breaking method for quickly detecting disease in tomato plants. The 4 corners of all tomato plants were captured using an image-capture box to locate and detect leaf infection. A tomato variety known as Diamante Max is selected as the test data. The method was designed to identify three diseases in tomatoes. CNN was utilized by the system to determine which tomato illnesses were present on the plants being watched.However, the primary issue with growing roses is the illnesses that might impede their growth because they harm the plant's leaves (Khaleel et al., 2022). To identify the four kinds of diseases mentioned above on rose plant leaves, the suggested work uses the CNN model. Some of the images come with an existing data set, while others were taken in the actual field. Before training using CNN with the optimal settings, the dataset was preprocessed.

2. Material and Methods

For this study, a collection of 559 images from the Mendeley databases is gathered. There are images of both healthy and sick pomegranate leaves in this collection. The processes that are done to find the best DL algorithm for pomegranate leaf disease detection are pictorially represented as a flowchart in figure 1.

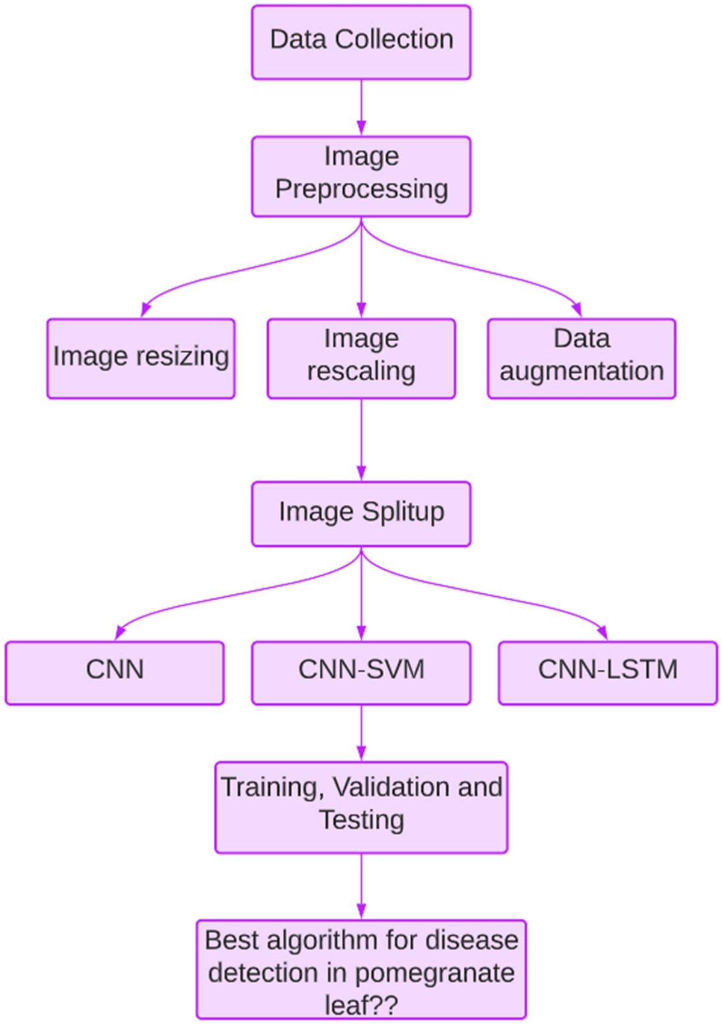


Fig. 1: Workflow of pomegranate leaf disease detection

Image resizing, image rescaling, and data augmentation are all included in the preprocessing. After preprocessing, the images are used to train the built-in DL models. Three algorithms are used in the modeling process. The algorithms are CNN, CNN-SVM, and CNN-LSTM. All three models use the same number of images for training and validation. The models are evaluated for the final metrics after training and validation. Accuracy, TPR, TNR, FPR, and FNR are some of the measures that were used in this study. Based on the test results, a confusion matrix was created. The test results provide the best algorithm for pomegranate leaf disease identification.

3. Data collection and preprocessing

The images that are used to test and train the DL models play a vital role in determining the performance of the algorithm (Masoot et al., 2022). This is because the models can work on images of various dimensions and layouts only when they're trained to work on various kinds of images. In this study, a dataset of images containing pomegranate leaves is used. This dataset has a collection of both disease-infected images and healthy images. The sample of images in the obtained dataset is given in table 1.

Table 1: Sample images of pomegranate leaf

Healthy	
Disease s	

From table 1, the difference between a healthy pomegranate leaf and a disease-affected leaf can be spotted. However, the number of both types of images has to be the same for the DL model to be not biased. The dataset obtained was composed of a total of 559 images. Not all images are used in this study. The split up of the images used in this study is shown in table 2.

Table 2: Number of images used in the study

LeafImage	**Available**	**Taken**
Total	559	540
Healthy	287	270
Diseases	272	270

Though the number of available images does not have equal parts of healthy and disease-affected images, the difference is not very large. Thus, a number that is close to the lesser is chosen. In this case, 270 images of each type are taken for training and testing the model. The images are then split into the ratio of 7:2:1. The larger part is used for training the DL models. The second large part is used for validation and the smallest of all is used to test the model for one last time. But before the steps like training and validation, the images are preprocessed to ensure the proper working of the model. The preprocessing includes three steps, image resizing, image rescaling, and data augmentation. These steps are explained below.

A. Image Resizing

Processing a tiny image yields better results for each DL model. The size of the dataset's images is reduced as a result. Further, this resizing process improves model performance by keeping the same size across all of the images in the dataset. In image resizing, a particular pixel that is more suitable for the DL models is selected and all the images are manipulated to be in that particular dimension (Yuriarti et al., 2016). In this study, all the images are resized to a dimension of 256*256. This standard sizing ensures uniformity and increases the efficiency of the performance of the DL models.

B. Image Rescaling

The process of adjusting the size of a digital image is known as "scaling" in the field of digital image processing.Remapping can be performed to fix image distortion or flip animage, whereas image scaling is required when you need to adjust the total amount of pixels (Chen et al., 2021). In other words, image scaling only modifies the print size of the image while maintaining the original image's pixel count. In this study, the images are scaled from 0 to 1. Just like image resizing, image rescaling also ensures uniformity and results in better working of the DL model.

C. Data augmentation

Increasing the number of images in a dataset is accomplished using a preprocessing technique called augmentation.making adjustments that won't interfere with the prediction process's flow, this technique multiplies the dataset's current images (Xu et al., 2020). Only the training images are subjected to the augmentation process. This is because a DL model's effectiveness is inversely related to the amount of the training dataset. Generally, data augmentation is performed only on the training dataset. The amount of data before and after augmentation is shown in table 3.

Table 3: Data before and after augmentation

Data	**Train (Before augmentation)**	**Train (After augmentation)**	**Validate**	**Test**
Healthy	189	500	54	27
Diseases	189	500	54	27

From table 3, it can be inferred that the number of images used in training drastically increased after augmentation. This increased number of images can produce a great advantage in the performance of the model after training. For a clearer understanding, the data before and after the augmentation process is plotted as a bar graph and is shown in figure 2.

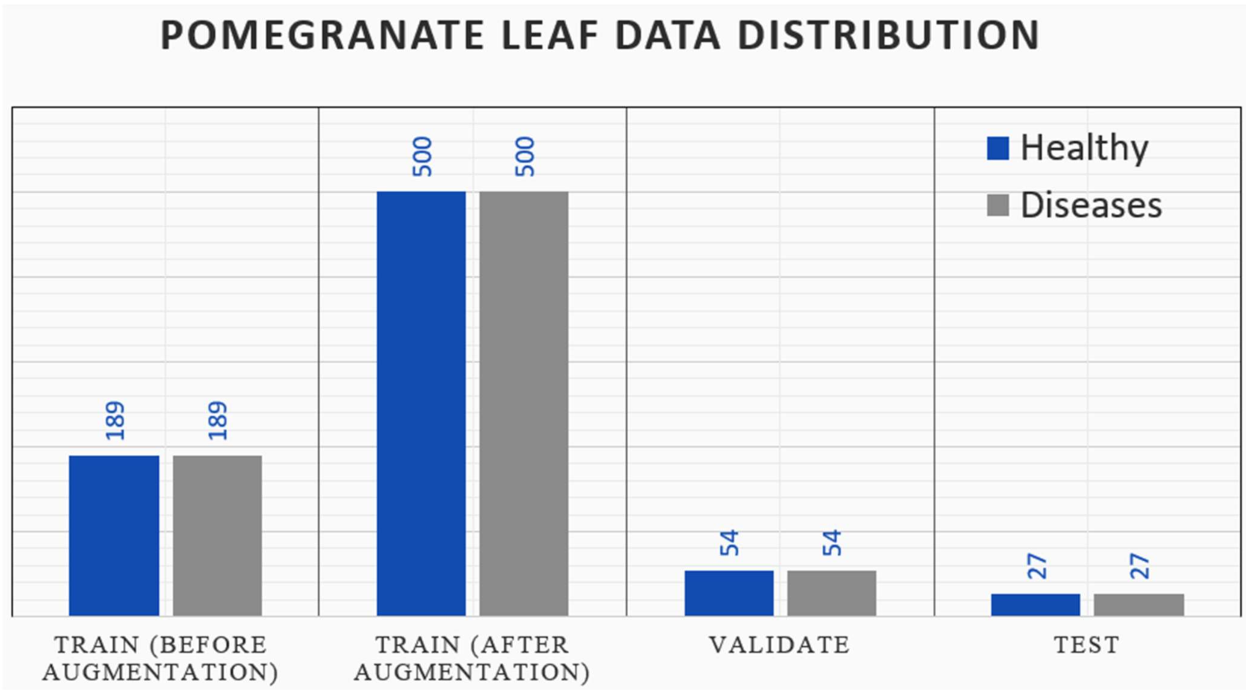


Fig. 2: Distribution of data

It can be seen that the number of images used for training after augmentation is higher than the doubled number before augmentation. As mentioned earlier, after training, the model can perform much better because of the increased number of images.

4. **DL Models**

A. Convolutional Neural Network (CNN)

The DL model is a crucial part of this research. The first algorithm which was chosen to be trained to predict pomegranate leaf disease is the CNN algorithm. The CNN algorithm is a part of a broad classification called the Neural Networks which is particularly used in applications that requires the recognition of image and voice (Lee et al., 2019). The CNN algorithm is specifically used for image recognition. The CNN algorithm is a supervised algorithm which makes it more efficient. One of the major benefits of this approach is the reduction in the number of layers that need to be defined thanks to the integrated convolutional layer (Kolias et al., 2021). When an algorithm has to be designed from scratch, it requires a lot of time and expertise. But as CNN comes with a predefined architecture that only requires slight modification according to the user requirements. Four layers are usual for a finalized

CNN model. Its inbuilt convolutional layer decreases the dimension of images while retaining all information.

B. Convolutional Neural Network – Support Vector Machine (CNN-SVM)

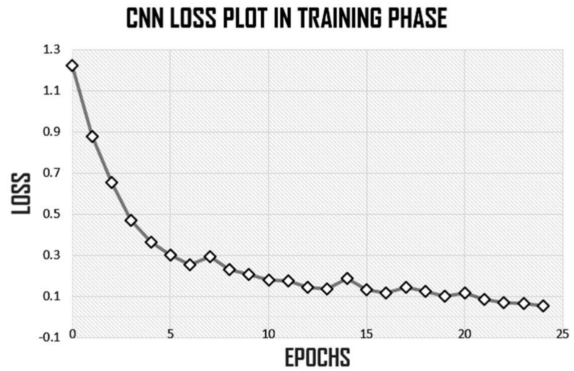
This model is a combination of two different DL algorithms. The algorithms include CNN and SVM. The CNN is employed for FE from the leaf images and identification of disease using SVM Using the SVM approach, classification problems involving massive data can be resolved more quickly. This classic approach to DL continues to be a very efficient strategy. In the area of big data, SVM in especially can be utilized to handle multi-domain tasks(Saidi et al, 2021). The SVM is an algorithm for supervised ML. An SVM training method generates a system that predicts the group of a current instance from a set of training examples, every of which has been allocated to one of the several categories.SVM is more effective at generalizing issues when it comes to statistical learning.Making predictions and judgments using the SVM algorithm is simpler when using the statistical learning theory (Biswas et al., 2021). The SVM is considered one of the easiest algorithms to use for categorizing images. There are two types of image classification in the support vector machine approach. Both linear and non-linear patterns are present.

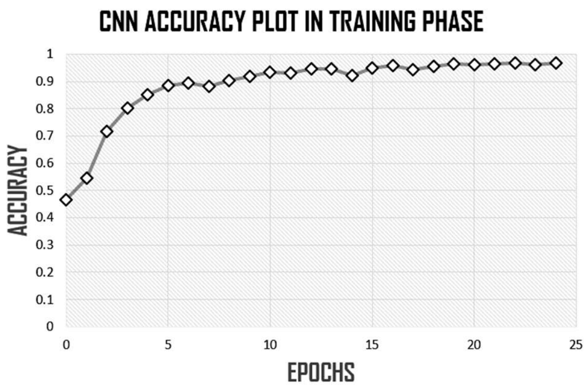
C. Convolutional Neural Network-Long Short-Term Memory network (CNN-LSTM)

This model is again a combination of the CNN algorithm with the LSTM algorithm. This algorithm was created with three main goals in mind (Lieng et al., 2020). Image description, activity recognition, and video description are three examples of them. The CNN model serves as the first layer in this combination, and the LSTM model serves as the second layer. The model is more effective because there are multiple DL algorithms present. To ensure optimal operation, the model additionally includes a dense layer in addition to the LSTM layer (Wenya, 2021). The algorithm's key benefit is FE. This quality makes it possible to analyze the image completely, leading to more encouraging results.

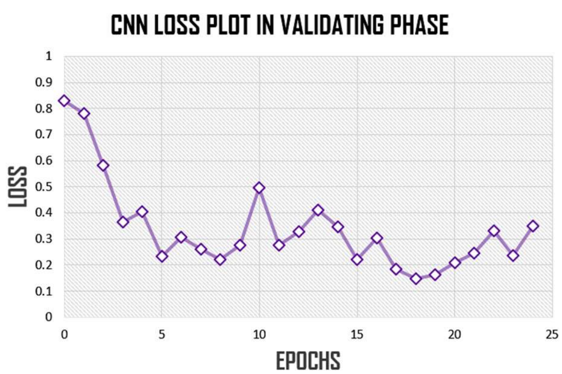
5. Results and Discussions

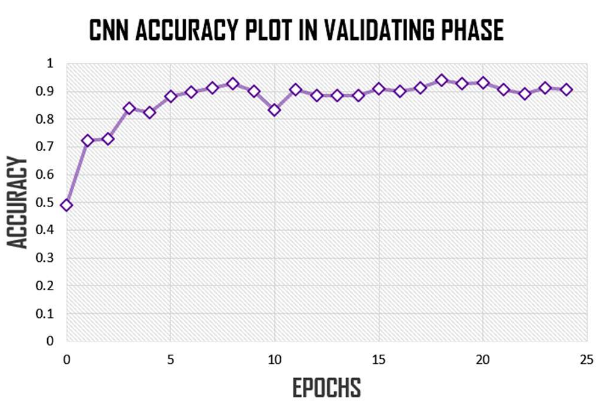
The main objective of this study is to find out which DL model can provide greater performance in image processing when it comes to detecting the presence of a disease in a pomegranate leaf. For this purpose, a dataset composed of 559 images is collected from the Mendeley datasets. This dataset contains images of pomegranate leaves – both healthy and disease-affected. Out of which 540 images are chosen to test, train and validate the DL models. But before the above-mentioned processes take place, the images are preprocessed. This preprocessing ensures the proper working of the DL models. After preprocessing, the images are used to train the constructed DL models. Three algorithms are used in the development of the models. The algorithms are CNN, CNN-SVM, and CNN-LSTM. All three models are trained using the same number of images. The validation step is followed by the training. The performance of the CNN model in both training and validation is depicted in figure 3





a) b)

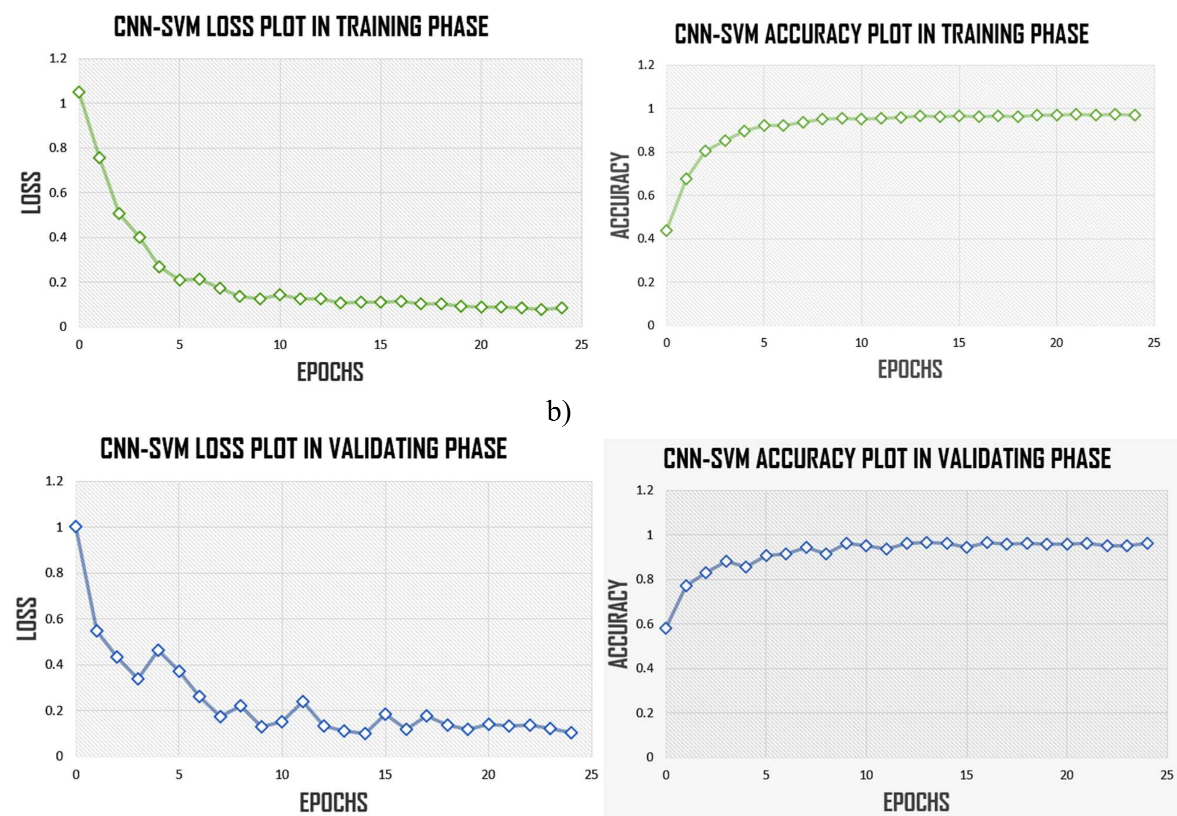




c) d)

Fig. 3: Performance of the CNN model

The performance of the CNN-SVM model is depicted in figure 4. The loss value is relatively high in the early training epochs, as can be seen in 4.a. However, when the number of epochs rose, it was severely reduced. The accuracy value is similarly applicable and is shown in 4.b. As the number of epochs rises, the model's accuracy similarly rises, from 50 to 90%. However, the validation shows that the model is inconsistent throughout the loss analysis even though the loss value reduces as the number of epochs rises which is given in 4.c. However, there were no significant changes to the accuracy in 4.d.



a) b)

c) d)

Fig. 4: Performance of the CNN-SVM model

Figure 5 explains the effectiveness of the CNN-LSTM algorithm in training and validation. As observed in 5. a, the model's loss value is fairly large during the first few training epochs. As the number of epochs rose, it was, however, substantially reduced. Similar considerations apply to the accuracy value, which is shown in 5.b. The model's accuracy similarly rises as the number of epochs does, from less than 50 to more than 90%. Unlike the other two models, the CNN-LSTM model does not cause a lot of fluctuations during validation, that is clear from figure 5.c. The accuracy was preserved in figure 5.d and the accuracy reaches 99% form the epochs of 10.

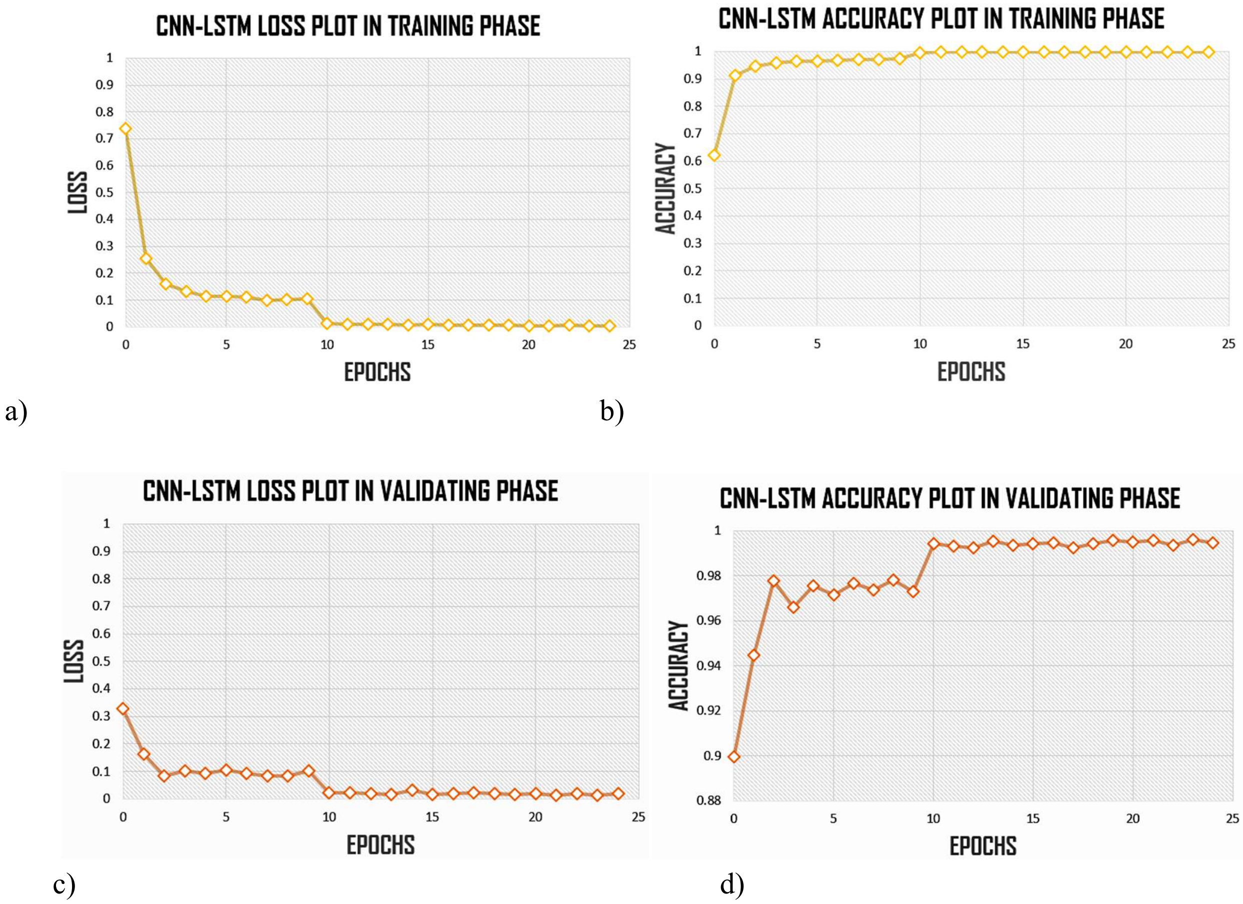


Fig. 5. Performance of the CNN-LSTM algorithm

After training and validation are completed, the models are tested with 27 images for each model. The performance of the models during the testing is analyzed using a confusion matrix and five metrics. The metrics include accuracy, TPR, TNR, FPR, and FNR. The formulae used to calculate the performance metrics are as follows.

$$Accuracy = \frac{Totalcorrectprediction}{TotalPrediction} \quad [1]$$

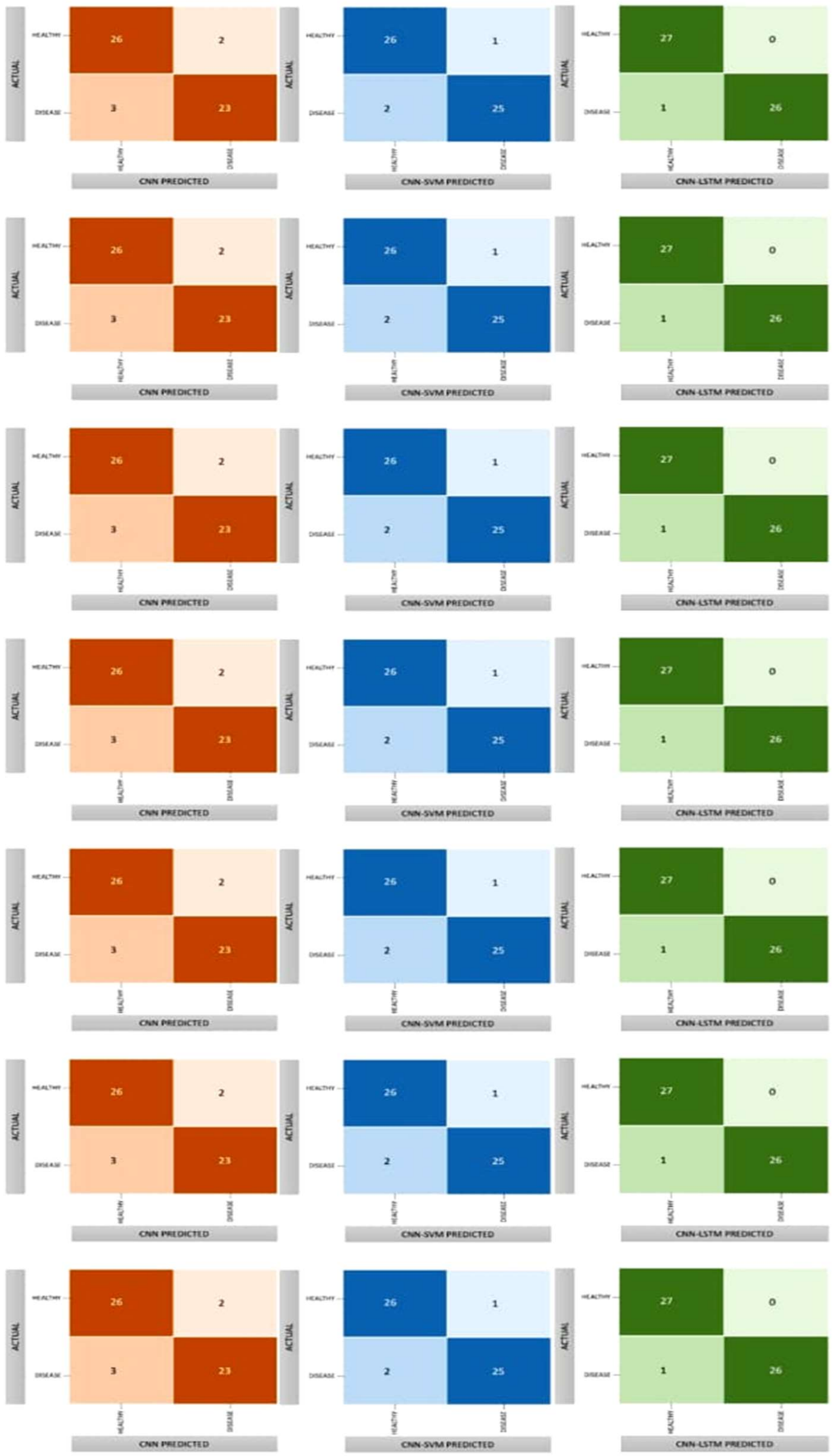
$$TPR = \frac{True\ positive}{Actual\ Positive} \quad [2]$$

$$FNR = \frac{False\ Negative}{Actual\ Positive} \quad [3]$$

$$TNR = \frac{True\ Negative}{Actual\ Negative} \quad [4]$$

$$FPR = \frac{False\ Positive}{Actual\ Negative} \quad [5]$$

As mentioned before, the confusion matrix recorded for the model developed using all three algorithms is shown in figure 6.



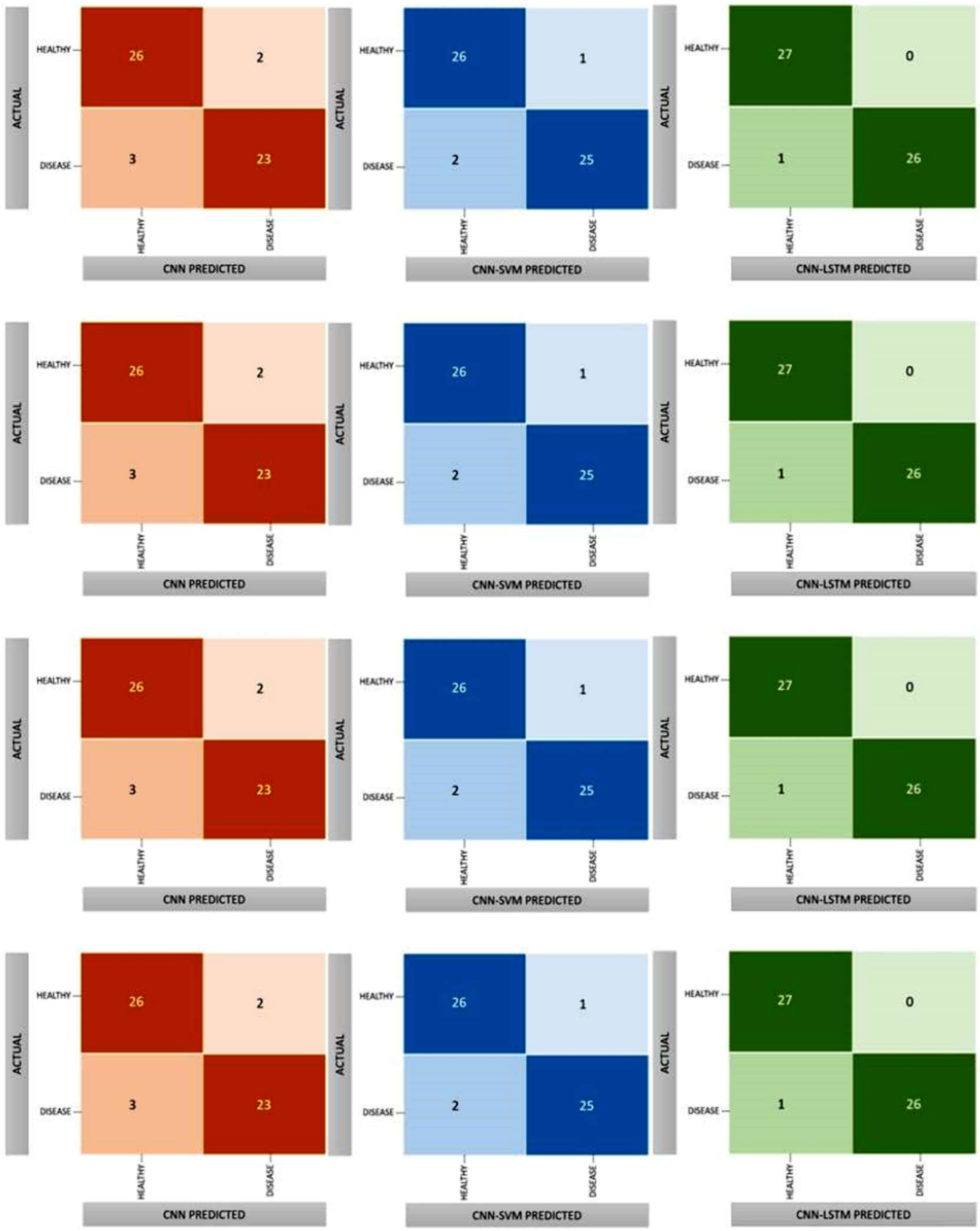


Fig. 6: Confusion matrix for DL models

For the CNN model, out of all 27 healthy images, the model predicted 25 of them as right and 2 as disease-affected leaves. For the disease affected, it predicted three of them wrong. Out of the 27 images of healthy leaves, the CNN-SVM model predicted that 26 were correct and 1 was an afflicted leaf. It incorrectly predicted two each for the affected condition. Out of the 27 healthy images, the CNN-LSTM model correctly predicted every single one of them. It made just one incorrect prediction for the condition in question. The accuracy and performance metrics are calculated based on the confusion matrix and the above-mentioned formulae. These values are tabulated and shown in table 3.

Table 3: Performance metrics during testing

MODEL	ACCURACY	TNR	TPR	FNR	FPR
CNN	90.7407	92.8571	88.4615	11.5385	7.14286
CNN-SVM	94.4444	96.2963	92.5926	7.40741	3.7037
CNN-LSTM	98.1481	100	96.4286	3.57143	0

From table 3, it can be seen that the CNN-LSTM model has a great advantage over the other two algorithms. A few of the notable points about that algorithm are that it has a complete true negative rate and a null false positive rate. Meanwhile, the CNN algorithm is found to be the weakest among the bunch. It is understandable because the other two models are a combination of two different models when the CNN is an individual algorithm.

An image processing model is considered efficient when it can properly predict a real-time image that is not a part of the training dataset. The performance of the CNN-LSTM model with such an image is shown in figure 7.

Fig. 7: Performance of the CNN-LSTM model

From figure 7, it can be seen that the model can predict all images correctly with no errors. It is also observed that the model is predicted correctly even when the images are flipped/mirrored.

6. Conclusions

Finding out whether a DL model can perform better in image processing when it comes to identifying the existence of a disease in a pomegranate leaf is the major goal of this study. A dataset of 559 images is gathered for this purpose from the Mendeley databases. This collection includes images of both healthy and diseased pomegranate leaves. Out of these 540 images are selected for the DL models' testing, training, and validation. However, the images must first go through preprocessing before the aforementioned operations can begin. This preprocessing guarantees that the DL models will operate correctly. The preprocessing includes image resizing, image rescaling, and data augmentation. The image resizing and rescaling steps ensure that the images are of the same size, dimensions, and pixels to ensure uniformity. The data augmentation step enhances the number of images in the training dataset. This step lengthens the training process and increases the performance of the DL models. The images are utilized to train the built-in DL models after preprocessing. The creation of the models makes use of three algorithms. CNN, CNN-SVM, and CNN-LSTM are the algorithms. The same number of imagesis used for training and validation across all three models. After training and validation, the models are tested for the final metrics. The parameters that are used in this study include accuracy, TPR, TNR, FPR, and FNR. A confusion matrix was also designed based on the test performance. In the end, it is found that the CNN-LSTM algorithm can provide a better accuracy value than the other two algorithms. The performance of the model is also analyzed by a real-time image for one last time. In the future, this study is expected to be updated with the additional feature of detecting the type of disease along with the prediction. Also, the dataset used in this study is expected to be replaced by real-time images instead of the one obtained from the internet to increase the efficiency of prediction.

References

1. Sardogan, Melike, AdemTuncer, and YunusOzen. "Plant leaf disease detection and classification based on CNN with LVQ algorithm." In 2018 3rd international conference on computer science and engineering (UBMK), pp. 382-385. IEEE, 2018.
2. Chen, Si, Fang Lv, and Ping Huo. "Improved detection of yolov4 sunflower leaf diseases." In 2021 2nd International Symposium on Computer Engineering and Intelligent Communications (ISCEIC), pp. 56-59. IEEE, 2021.
3. Srinidhi, V. V., Apoorva Sahay, and K. Deeba. "Plant pathology disease detection in apple leaves using deep convolutional neural networks: Apple leaves disease detection using efficientnet and densenet." In 2021 5th international conference on computing methodologies and communication (ICCMC), pp. 1119-1127. IEEE, 2021.
4. Yusoff, NorfarahinMohd, Ili Shairah Abdul Halim, and Noor Ezan Abdullah. "Real-time hevea leaves diseases identification using Sobel edge algorithm on FPGA: A preliminary study." In 2018 9th IEEE Control and System Graduate Research Colloquium (ICSGRC), pp. 168-171. IEEE, 2018.
5. Prakash, R. Meena, G. P. Saraswathy, G. Ramalakshmi, K. H. Mangaleswari, and T. Kaviya. "Detection of leaf diseases and classification using digital image processing." In 2017 international conference on innovations in information, embedded and communication systems (ICIIECS), pp. 1-4. IEEE, 2017.
6. Bodhe, Ketan D., Himanshu V. Taiwade, Virendra P. Yadav, and Nikesh V. Aote. "Implementation of Prototype for Detection & Diagnosis of Cotton Leaf Diseases using Rule Based System for Farmers." In 2018 3rd International Conference on Communication and Electronics Systems (ICCES), pp. 165-169. IEEE, 2018.

7. Jianqing, Huang, Yuan Qi, Liu Debing, and Zhang Jiarong. "Research on Banana Leaf Disease Detection Based on the Image Processing Technology." In 2022 IEEE 5th International Conference on Computer and Communication Engineering Technology (CCET), pp. 76-79. IEEE, 2022.
8. Ashok, Surampalli, Gemini Kishore, Velpula Rajesh, S. Suchitra, SG Gino Sophia, and B. Pavithra. "Tomato leaf disease detection using deep learning techniques." In 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 979-983. IEEE, 2020.
9. Li, Xin, and Laxmisha Rai. "Apple leaf disease identification and classification using resnet models." In 2020 IEEE 3rd International Conference on Electronic Information and Communication Technology (ICEICT), pp. 738-742. IEEE, 2020.
10. Padol, Pranjali B., and S. D. Sawant. "Fusion classification technique used to detect downy and Powdery Mildew grape leaf diseases." In 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC), pp. 298-301. IEEE, 2016.
11. Sunitha, Gurram, K. Reddy Madhavi, J. Avanija, S. Tharun Kumar Reddy, and R. Hitesh Sai Vittal. "Modeling Convolutional Neural Network for Detection of Plant Leaf Spot Diseases." In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1187-1192. IEEE, 2022.
12. Metre, Vishakha A., and Sudhir D. Sawarkar. "Reviewing important aspects of plant leaf disease detection and classification." In 2022 International Conference for Advancement in Technology (ICONAT), pp. 1-8. IEEE, 2022.
13. Indumathi, R., N. Saagari, V. Thejuswini, and R. Swarnareka. "Leaf disease detection and fertilizer suggestion." In 2019 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 1-7. IEEE, 2019.
14. De Luna, Robert G., Elmer P. Dadios, and Argel A. Bandala. "Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition." In TENCON 2018-2018 IEEE Region 10 Conference, pp. 1414-1419. IEEE, 2018.
15. Khaleel, Mohammad Ibrahim, Paineni Gowtham Sai, Adabala Uday Raghavendra Kumar, Purushothamman Raja, and Vinh Truong Hoang. "Rose Plant Leaves: Disease Detection and Pesticide Management using CNN." In 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1067-1072. IEEE, 2022.
16. Masood, Rao Farhat, Taimur Hassan, Hina Raja, Bilal Hassan, Jorge Dias, and NaoufelWerghi. "A Composite Dataset of Lumbar Spine Images with Mid-Sagittal View Annotations and Clinically Significant Spinal Measurements." In 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2), pp. 1-5. IEEE, 2022.
17. Yuniarti, Anny, StefanusAnggara, and BilqisAmaliah. "Resize my image: a mobile app for interactive image resizing using multi operator and interactive genetic algorithm." In 2016 International Conference on Information & Communication Technology and Systems (ICTS), pp. 58-62. IEEE, 2016.

18. Chen, Yan-An, Ching-Chun Hsiao, Wen-Hsiao Peng, and Ching-Chun Huang. "Direct: Discrete image rescaling with enhancement from case-specific textures." In 2021 International Conference on Visual Communications and Image Processing (VCIP), pp. 1-5. IEEE, 2021.
19. Xu, Hao, Chen Li, Md MamunurRahaman, Yudong Yao, Zihan Li, Jinghua Zhang, Frank Kulwa, Xin Zhao, Shouliang Qi, and Yueyang Teng. "An enhanced framework of generative adversarial networks (EF-GANs) for environmental microorganism image augmentation with limited rotation-invariant training data." IEEE Access 8 (2020): 187455-187469.
20. Lee, Mi-Young, Joo-Hyun Lee, Jin-Kyu Kim, Byung-Jo Kim, and Ju-Yeob Kim. "The sparsity and activation analysis of Compressed Cnn networks in a hwcnn accelerator model." In 2019 International SoC Design Conference (ISOCC), pp. 255-256. IEEE, 2019.
21. Kollias, Dimitrios, and Stefanos Zafeiriou. "Exploiting multi-cnn features in cnn-rnn based dimensional emotion recognition on the omg in-the-wild dataset." IEEE Transactions on Affective Computing 12, no. 3 (2020): 595-606.
22. Saidi, Afef, Slim Ben Othman, and Slim Ben Saoud. "A novel epileptic seizure detection system using scalp EEG signals based on hybrid CNN-SVM classifier." In 2021 IEEE Symposium on Industrial Electronics & Applications (ISIEA), pp. 1-6. IEEE, 2021.
23. Biswas, Angona, and Md Saiful Islam. "Hybrid CNN-SVM Model for Brain Tumor Classification utilizing Different Datasets." In 2021 International Conference on Electronics, Communications and Information Technology (ICECIT), pp. 1-4. IEEE, 2021.
24. Liang, Shengbin, Bin Zhu, Yuying Zhang, Suying Cheng, and JiangyongJin. "A Double Channel CNN-LSTM Model for Text Classification." In 2020 IEEE 22nd International Conference on High Performance Computing and Communications; IEEE 18th International Conference on Smart City; IEEE 6th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), pp. 1316-1321. IEEE, 2020.
25. Wenya, Liu. "Cooling, heating and electric load forecasting for integrated energy systems based on CNN-LSTM." In 2021 6th International Conference on Power and Renewable Energy (ICPRE), pp. 808-812. IEEE, 2021.