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A Hybrid AlexNet-ShuffleNet framework for plant leaf disease detection

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Abstract
The study proposes a Hybrid AlexNet-ShuffleNet framework for plant leaf disorder identification. The investigational outcomes prove that the presented hybrid approach outperforms both AlexNet and ShuffleNet in terms of specificity, accuracy and sensitivity. The model offers practical applicability for farmers and plant disease researchers to detect and prevent crop losses caused by plant leaf diseases. The hybrid model proposed in the study combines the advantages of both AlexNet and ShuffleNet, resulting in improved accuracy compared to the individual networks. AlexNet excels in learning high-level features, while ShuffleNet specializes in reducing the computational difficulty of deep neural networks. The hybrid technique leverages these strengths with the RoI extracted to enhance the overall performance of the procedure. The projected scheme reached maximum accuracy rate of 95.09%, sensitivity rate of 97.98% and specificity rate of 93.93%. Overall, the hybrid framework has the potential to be a valuable tool for agricultural production in the recognition and prevention of plant leaf disorder.

Keywords Disease detection · Plant disease · Deep learning · AlexNet · ShuffleNet

Abbreviations

K-NN	K-nearest neighbors
SVM	Support vector machines
DL	Deep learning

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IoT	Internet of Things
ML	Machine Learning
CNN	Convolutional Neural Networks
LBP	Local Binary Pattern
ALDD	Apple Leaf Disease Dataset
VRNet	Variant Residual Network
SE	Squeeze-and-Excitation
BN	Batch Normalization

1 Introduction

In precision agriculture, the identification of plant diseases via image analysis is a critical research area. Previously, experts visually assessed the severity of diseases in plants. However, with advances in information technology and the widespread use of digital cameras in agriculture, expert systems for cultivation and management have become popular, significantly improving plant production [1]. Since plants are essential to human survival, it is crucial to adopt rigorous approaches for identifying and analyzing plant diseases [2]. Presently, expert systems for detecting and describing disease characteristics rely heavily on the expertise of professionals, leading to high expenses and low efficiency [3, 4]. Typically, plants are susceptible to viral, bacterial, and fungal diseases, like brown spot, Downey mildew, powdery mildew, bacterial blight, and leaf rust [5, 6]. Thus, early diagnosis is crucial in reducing the damage caused by the diseases. However, continuous monitoring by professionals can be expensive and time-consuming, making it impractical for farmers [7]. An accurate, fast, and cost-effective method to detect diseases from the symptoms that arise on the plant leaves is thus vital. Machine vision offers automatic image-based inspection, process control, and robot guidance [8]. While traditional methods of recognizing and diagnosing plant diseases using human eyes can be inaccurate, time-consuming, and expensive, deep learning techniques offer rapid and preciserecognition and categorization of plant disorders [9]. Using photographic images of plant infections'symptoms, clinicians can study, teach, analyze, and diagnose plant diseases [10].

Identification and categorization of plant disorder using Artificial Intelligence (AI) strategies is a prevalent practice. K-NN, logistic regression, decision trees, and SVM are some of the most widely used algorithms to achieve this goal [11]. These algorithms combine with various image pre-processing methods to enhance feature extraction. K-NN, a supervised learning algorithm, uses similarity measures to classify data. Unlabeled objects get classified based on the classification of neighboring labeled objects [12]. In contrast, decision trees are learning algorithms that use flow charts to represent decision attributes and outcomes. The classes of leaves are represented as branches on the flow chart. Despite their usefulness, decision trees have limitations, such as overfitting and overlapping nodes [13].

DL is a subset of ML that stands out due to its exceptional ability to classify and identify patterns [14]. Within the agricultural industry, DL procedures like recurrent neural networks, CNNs, and deep belief networks have received widespread adoption to execute tasks such as crop recognition, predicting yield quantity, and crop infectionidentification [15, 16]. Among these methods, CNNs are preferred due to their ability to dig out semantic demonstrations from input examples and learn spatial hierarchies [17, 18]. CNN frameworks can process and extract critical data from training datasets automatically, leading to better decision-making processes without human intervention [19]. Several recent studies have employed DLs for crop disease recognition and classification across various crops such as rice, grapes, tomatoes, potatoes, cucumbers, and maize [20, 21]. These studies utilize advanced CNN architectures inclusive of DenseNet, AlexNet, and ResNet, and transfer learning to detect crop diseases while also proposing novel CNN architectures to enhance disease detection and classification accuracy [22]. The approach offers highly precise results while requiring minimal pre-processing and computing costs [23]. Also, DL algorithms use topological information to process input images, making them highly robust to modifications, including scaling, rotation, and translation, making them ideal for various purposes [24].

Since prematureidentification of plant disorder is crucial to preventing the spread of diseases and reducing crop losses, the use of DL techniques for plant disease recognition has become popular in recent years. However, the high computational cost and memory requirements of these models remain significant challenges, limiting their adoption in resource-limited settings. To overcome these challenges, the study proposed a hybrid AlexNet-ShuffleNet framework for plant leaf disorder identification that combines the strengths of two neural network architectures to improve detection accuracy. The proposed framework is built on a synergistic combination of AlexNet and ShuffleNet architectures, incorporating their respective strengths in feature extraction and computational efficiency. The proposed framework is trained and tested on a collective dataset comprising plant leaf diseases and has achieved high detection accuracy, outperforming existing state-of-the-art strategies. The introduced Hybrid AlexNet-ShuffleNet structure for plant leaf infection recognition has the potential to enable early detection of plant diseases in resource-limited settings, reducing crop damage and boosting agricultural productivity.

The key objectives of thestudy:

- To extract the Region of Interest (RoI) using CNN so as to locate the diseased region in the plant leaf.
- To detect the plant leaf disease, the hybrid AlexNet-ShuffleNet framework is proposed. The main advantage of the ShuffleNet is that it uses to decrease computation expenditure while preserving precision, and also AlexNet uses the ReLU activation function which doesn't suffer from the Vanishing Gradient (VG) problem. Thus, the hybridization of AlexNet-Shuffle Net is performed in this work.
- To investigate the performance of the presentedapproach, the metrics, such like specificity, accuracy, RoC and sensitivity isapplied and compared with the existing works.

The paper is arranged in the way as below: Section 2 offers a brief description of the previous research related to plant disease detection. The presented Hybrid AlexNet-ShuffleNet-based plant disease detection is depicted in Section 3. In Section 4, the discussion and findings of the approach introduced are examined. At last, in Section 5, the conclusion of the developed technique is given.

2 Literature survey

The segment below offers an brief description of the existing studies associatedwith the detection of plant diseases.

Hosny Khalid M et al., [3], examined aninsubstantial deep CNN model for extracting high-level veiled feature depictions from plant leaf images. The research employed conventional handcrafted LBP factors to detect local texture information in the images. The presentedstrategy was trained and evaluated on datasets that are publicly accessible, including Grape Leaf, Tomato Leaf, and Apple Leaf, demonstrating excellent results for plant disease detection. In another study, Vishnoi Vibhor Kumar et al., [13], examined a CNN strategy to classify Scab, Cedar rust, and a Black rot disease in apple leaves utilizing the PlantVillage dataset. The model is designed with fewer layers to reduce computational burden, with some augmentation techniques utilized to producefurther samples, thereby increasing the training set. Consequently, the model takes fewer system resources and has less implementation time than numerous other deep CNN approaches with similar accuracy. The described models offer an effective tool for crop disease detection, specifically handheld devices, and can assist farmers in making informed decisions to maximize crop yield.

In a research paper by Masood Momina et al., [24], a DL strategy, MaizeNet, was introduced for precise localization and categorization of several maize crop leaf infections. The authors utilized an enhanced Faster-RCNN approach, incorporating the ResNet-50 technique with spatial-channel consideration, to compute deep keypoints that were then categorized into various classes of diseases. The presented approach was examined on the Severity and Corn Disease database, containing examples from three maize plant disease classes captured under complex and diverse conditions. Similarly, Shovon Md Sakib Hossain et al., [2], presented a robust deep ensemble approach, PlantDet, based on InceptionResNetSV2, Xception, and EfficientNetV2L. Utilizing efficient data augmentation, preprocessing, and multiple layers, including a L2 regularizers, PReLU activation function, Global Average Pooling layer, and more Dense layers, the authors successfully tackled overfitting and underfitting issuesalthoughpreservingelevated performance. The model was tested on the Betel Leaf dataset and outperformed existing strategies, containing robust ensemble techniques. Additionally, Score-CAM and Grad-CAM techniques were employed to clarify the method'seffectiveness and convoluted on how DL models function for this composite dataset. In summary, the presented models in both studies hold promise for precise disease detection and classification, contributing to mitigating losses in crop productivity.

Sunil C. K et al., [1], conducted a study focused on detecting two disorders of cardamom plants, Phyllosticta Leaf Spot and Colletotrichum Blight, and three grape disorders, ESCA,Black Rot, and Isariopsis Leaf Spot. With deep learning being the preferred technique for plant disorderrecognition, the authors employed U2-Net to eliminateunnecessarysurroundings from input images by choosing multiscale factors. The presented approach utilized the EfficientNetV2 model for cardamom plant disease detection, and aninclusivesuite of trialswere conducted to evaluate its performance against additional approaches, likeCNN and EfficientNet. Similarly, Jiang Peng et al., [4], examined an improved DLstrategy based on CNNs for real-time apple leaf disease identification. The authors first constructed the ALDD using image annotation and data augmentation technologies and then introduced the Rainbow concatenation and GoogLeNet Inception structure to develop an apple leaf disorder identification technique that employed deep-CNNs. The presented INAR-SSD strategies wereskilled to distinguishthe common five apple leaf disorders, given that a high-performance resolution for the prematureidentification of these diseases using a dataset comprising 26,377 images of affectedleaves of apples. The results from both studies demonstrate the potential of deep learning techniques for accurate and efficient plant disease identification, which could contribute to enhancing crop yields and mitigating losses in agricultural production.

Xiao Zhiyong et al., [8], examined a lightweight model, SE-VRNet, for extraction of a further precise segment of lesion and interestaccording to an attention mechanism and superior residual network. The presented SE-VRNet used SE module and a deep VRNet along with attention mechanism to address the trouble of difficult feature extraction due to the detachedposition of leaf disorder. The investigationaloutcomes on the datasets of SelfData, NewData, OriData, and PlantVillage demonstrated that SE-VRNet outperformed other conventionalstrategies and showed feasibility and effectiveness in recognizing leaf disorder with mobile devices. Similarly, Amin Hassan et al., [6], developed an end-to-end DLstrategy for identifying unhealthy and healthy corn plant leaves even as considering the model's parameter numbers. The model utilized two pre-trained CNNs, DenseNet121and EfficientNetB0, to extort deep features from images of corn plant and combined them using concatenation to construct a composite feature set for better learning. Data augmentation techniques were applied to augment the dataset by introducing variations to images, allowing the model to learn more complex data cases. The attained results were compared with ResNet152 and InceptionV3, which have higher parameter and processing power requirements than the presented model. In summary, both studies exhibitthe prospective of DLtechniques in accurately and efficiently detecting plant diseases while reducing parameters and processing power requirements.

2.1 Challenges

From the challenges of the existing approaches stated in the aforesaid section, the research gaps found are enlisted as follows:

The lightweight CNN model and LBP approach in [1] are unsuccessful when applied to diagnose leaf diseases of other crops. The improved Faster-RCNN [3] failed to explore other deep learning approaches to enhance the classification results. The ensemble model exhibited in [4] handled the underfitting and overfitting issues; however, the training time taken is more. The deep-CNNs utilizing the GoogLeNet Inception structure and Rainbow concatenation method [6] lacked the inclusion of additional evaluation metrics, such as sensitivity and specificity. At last, Pre-trained CNN, EfficientNetB0 and DenseNet121 [8], proved ineffective while working with different feature extractors and fusion methods on the dataset.

3 Proposed AlexNet-ShuffleNet model for plant disease identificationand classification

In the process of identifying diseases that affect plants in order to prevent them from spreading and to minimize crop losses, this research endeavors to advocate a hybrid DL framework. This leaf disease detection technique mainly includes pre-processing, data augmentation, and plant leaf identification. At the outset, the input image is conceded to the pre-processing step. The input image is preprocessed with the intention to eliminate the noises and redundant pixels using median filter and image resizing. After that, the data augmentation was performed from the pre-processed image. Here, the data augmentation techniques employed was rotation, shearing, zooming, flipping, brightness adjustment [17]. Then, RoI is extracted to locate the diseased region in the leaves using CNN. At last, the plant leaf disorder detection procedureis completedby means of the hybrid AlexNet-ShuffleNet that is proposed by combining AlexNet [20] and ShuffleNet [12] framework to classify into healthy and unhealthy. In the case of unhealthy leaves, a classification is involved into subclasses using the hybrid AlexNet-ShuffleNet. Figure 1 demonstrates the architectural diagram of the leaf disorderrecognition using Hybrid AlexNet-ShuffleNet technique.

3.1 Preprocessing

Preprocessing involves anarray of actions in use to organizeunrefined data for additional-examination or representation. It is a crucial step in data examination, as it assists in cleaning, transforming, and organizing data into anarrangement that is effortlessly modeled or examined. Image resizing and median filtering are the methods used for preprocessing in this context. These methods help to organize and simplify the images, making it easier to analyze them further.

Image resizing When dealing with image processing, determining the appropriate image dimensions plays a crucial role in evaluating the performance of machine learning techniques. Images that are too large could guide to an extremeamount of model parameters and lengthier training times. On the other hand, images that are minute might end in the loss of pertinent features. In computer vision applications, like object identification or image

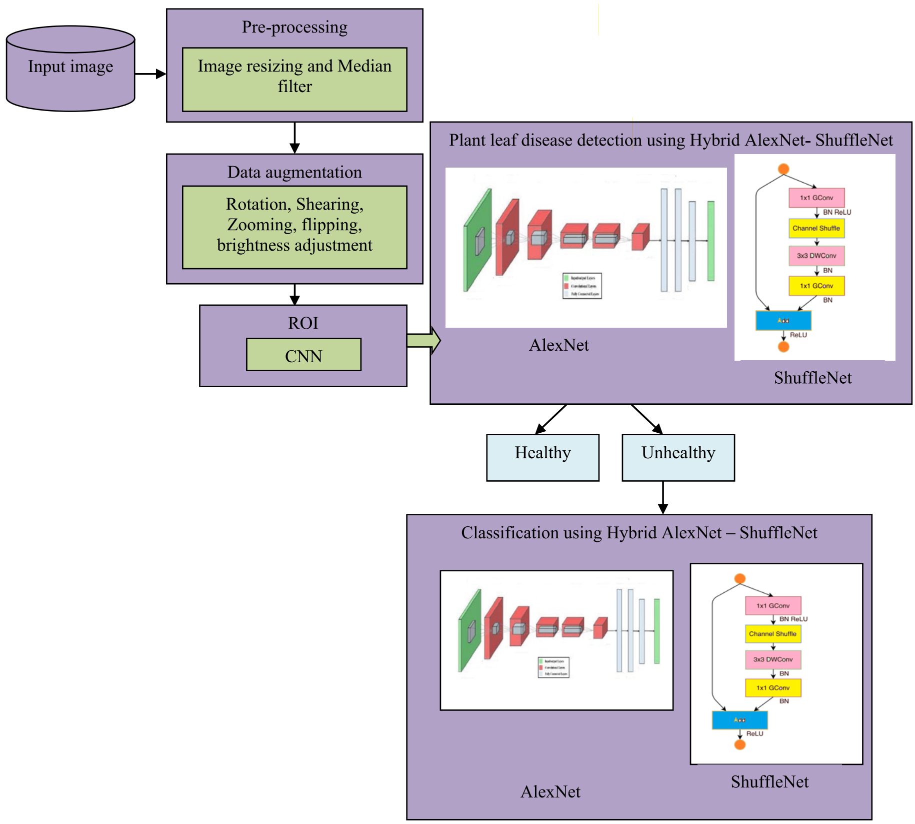


Fig. 1 Architectural illustration of the leaf disease recognition using Hybrid AlexNet-ShuffleNet technique

organization, it is common to resize images [14] as a preprocessing step. This involves scaling images to a standard size, which can decrease the complication of the algorithm and ensure coherence in the input data. In this study, we have resized the original leaf images to a dimension of 32 ×32 pixels. Moreover, image resizing can diminish the effect of minor dissimilarity in orientation, perspective, or image size, which can significantly concern the accuracy of the technique.

Median filter One of the most widely recognized order-statistics filters is the median filter [16]. This filter reinstates the rate of each pixel in an image with the median of the gray levels within that pixel's neighborhood.

$$\widehat{f}\left(p,q\right)=\underset{s,T\in s_{p,q}}{mendian}\left\{g\left(s,T\right)\right\} \tag{1}$$

Let $S_{p,q}$ denote an array of coordinates within a rectangular sub-image located at a certain point (p,q). It's worth noting that the unique pixel rate is taken into account when computing the median. Median filters are highly regarded due to their impressive noise reduction capabilities for certain kinds of arbitrary noise, and they accomplish this with much less blurring than similarly sized linear smoothing filters.

3.2 Data augmentation

Data augmentation [9] is a procedure used to augment the size of a dataset by creating new variations of the existing data. By mounting the amount of images in the dataset, the technique can be trained to be more flexible and be able to detect patterns that may differ from the ones in the original dataset. Data augmentation is a powerful technique that can help to progress the accuracy of MLtechniques trained on image datasets. A variety of techniques can be used to create completely new variations of the existing data, making it much harder for the model to overfit. This technique is particularly useful in image classification tasks, where it can help prevent overfitting and improve model accuracy. This involves applying transformations, such as rotation, shearing, zooming, flipping, and brightness adjustment to the original images. Images can be rotated at different angles to help the proposed model cope with variations in orientation and improve its generalization capability. Shearing involves skewing the image horizontally or vertically, which can introduce distortions that help the model learn to recognize the patterns of interest even in the presence of similar distortions. Zooming in and out of images is an effective way to simulate differences in scale and improve model performance on images captured at different distances. Images can be flipped horizontally or vertically to deal with differences in orientation and improve the model's ability to recognize the same disease in different settings. Brightness can be adjusted to simulate variations in lighting conditions, which can help the model become more robust to lighting changes. By applying these transformations to the original images, the proposed model can learn to recognize patterns of interest in a more robust and generalizable way. When rotated, scaled, or sheared, an image can appear to be a completely different image, which can augment the assortment of the dataset and make it more difficult for the model to overfit. Image flipping or changing brightness can also be used to create new images that can be added to the dataset.

3.3 Segmentation of diseased region using CNN

Region of Interest (RoI) extraction involves identifying and highlighting specific areas of an image that are of interest. This process is extensively used in various computer vision applications, such as object recognition, scene understanding, and medical image analysis. CNNs are powerful deep learning frameworks that provide a reliable and efficient approach to RoI extraction in computer vision applications. By learning features from images, CNNs [23] can accurately segment the image that helps in the disease detection task. CNN is a commonly used DL framework for recognition and image processing tasks, including RoI extraction. A CNN is a sort of a neural network that is considered to automatically learn features from images. It consists of multiple layers, counting pooling layers, convolutional layers, and fully connected layers. In a CNN, the image is fed into the input layer, and the convolutional layers extort features from the image using a set of filters or kernels. The pooling layers downsample the image to reduce its spatial size while the fully connected layers process the learned features to classify or predict the output. In RoI extraction using a CNN, the CNN is first trained on a dataset of images that contain objects or RoI. The convolutional layers learn to extort features from the input images, including prominent patterns and shapes that distinguish different objects or regions. After the CNN is trained, it is applied to a new image, and proposes candidate regions of interest. Then, the RoI pooling layer identifies the specific features of the region of interest extracted from the convolutional layer. The image segmentation using CNN is represented in Fig. 2.

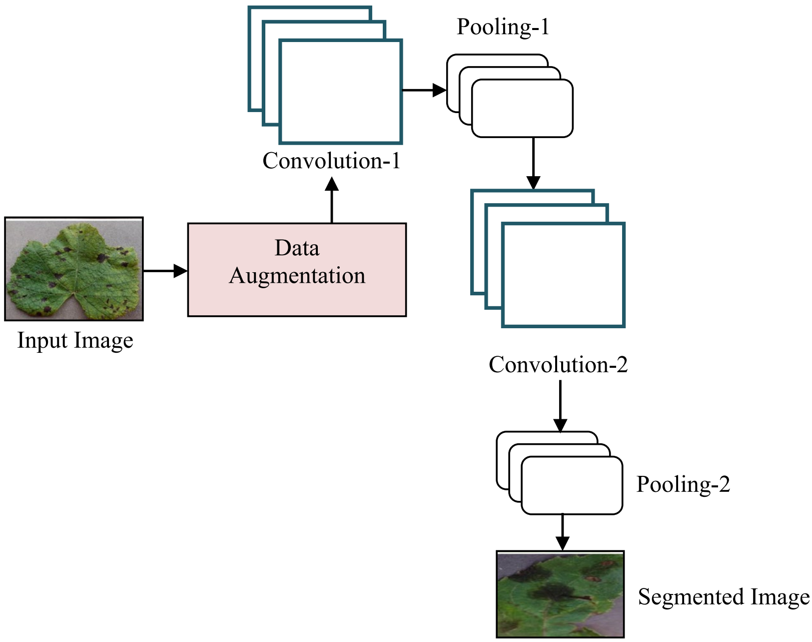


Fig. 2 Segmentation using CNN

3.4 Hybrid AlexNet-ShuffleNet

The study proposed a hybrid plant disease revealing model with the combination of two conventionalDL architectures, AlexNet, and ShuffleNet. The proposed hybrid model named Hybrid AlexNet-ShuffleNet aimed to benefit from the strengths of both architectures to improve the efficiency and accuracy of disease identification. AlexNet is a popular deep learning architecture that uses CNNs to extort features from images for classification tasks. RoI is extracted to locate the diseased region in the leaves using CNN. AlexNet is identified for its capability to handle high-resolution images effectively and extract rich visual features. ShuffleNet, on the other hand, is a lightweight deep learning architecture designed for efficient inference on mobile devices. ShuffleNet uses channel shuffle operation to reduce computational complexity, enabling it to perform well even with limited computational resources.

3.4.1 AlexNet

Deep neural networks consist of multiple hidden layers, which aid in improving feature extraction. As a result, these networks have proven to be highly effective for image classification, surpassing other methods. This has led to a surge in interest and usage of deep networks. AlexNet [22], a significant network consisting of 650,000 neurons and 60 million parameters, was one of the first to implement an improved activation function. Traditional neural networks were limited to activation functions, such as arctan, tanh, and logistic function for nonlinearity. However, these functions resulted in significant gradient values only for inputs within a small range around 0, leading to the problem of gradient vanishing. To address this issue, the rectified linear unit (ReLU) activation function was introduced. With ReLU, the gradient is always 1 if the input is greater than or equal to 0, and it accelerates the training process. The ReLU function can be defined through the following equation:

$$x = \max\left(0, y_1\right) \tag{2}$$

This network is comprised of multiple smaller sub-networks, each of which is susceptible to overfitting. To mitigate overfitting, the sub-networks share the same loss function, allowing for the dropping out of certain layers. Specifically, the fully connected layers are dropped out during training, resulting in a portion of the neurons being trained during each iteration. The forced cooperation between the neurons due to the dropout enhances the generalization and reduces joint adaptation between the neurons. The output of the complete network is the average of the sub-networks. This dropout method not only improves generalization but also increases robustness. The convolutional layers automatically extort features, which are then condensed by the pooling layer, given an image i with height a and width b. Here, n represents the convolutional kernel with height v and width c, and the convolution can be exemplified as follows:

$$c\left(a, b\right) = \left(i^{*} n\right)\left(a, b\right) = \sum_{u}\sum_{v} i\left(a - v, b - c\right) n\left(v, c\right) \tag{3}$$

The model is capable of learning from image features through convolution, with shared parameters employed to reduce model complexity. Pooling layers are utilized for further condense the extracted features. In AlexNet, max pooling is employed to diminish the feature map, where a 4 ×4 block is taken from the feature map to create a 2 ×2 block that includes the maximum rates. Feature generalization is enhanced using cross-channel normalization, a form of local normalization technique. Prior to feed the feature maps to the next layers, they are first normalized. The cross-channel normalization calculates a total from several adjacent maps with the same positions. The classification is carried out in the fully connected layers, using Softmax as an activation function, even can be compute using the following equation:

$$softmax\,(y)_I = \frac{\exp(y_I)}{\sum_{J=1}^{m} \exp(y_J)} \quad \text{for} \quad I = 0,1,2,\ldots,k \tag{4}$$

The softmax outcome comes under the range of 0 to 1, which is also the foremost benefits to make sure the activation of neurons; this is also the cause for taking the activation function.

3.4.2 ShuffleNet

ShuffleNet has employed group convolution rather than point convolution to improve network accuracy. By stacking group convolutions, the outputs of a particular group are dependent on the inputs within that group only, and the information flow between channels from different groups is blocked. However, in ShuffleNet, this problem is addressed by the shuffling operation, which obtains input data from dissimilar groups and completely interconnects the output and input channels. In order to optimize computational cost, ShuffleNet uses operations, such as depthwise convolution, pointwise group convolution, and shuffling operations. The unit with stride = 2 uses the AVG pooling technique with stride = 2 to enable connection between the output of the main path and the shortcut [5]. Within the main path of the ShuffleNet units, input channels pass through a Group Convolution (GConv) layer initially. The GConv layer ensures that each kernel examines only a few input feature maps and aggregates some information across the channels. In this architecture, GConv is used to reduce the computational complexity of 1 × 1 convolution. The GConv output is normalized using the BN technique and passed through the ReLU activation function. The BN technique is employed to ensure that the next layer receives the expected data shape as a result of the network weight change that happens after each step during gradient descent algorithm learning. This enables higher learning rates and less dropout to be utilized. To achieve normalization, each dimension of the d-dimensional data $l = l^{(1)}, l^{(2)}, \ldots, l^{(P)}$ is normalized using Eq. (5).

Equation (5) involves the per-dimension mean and variance of the data denoted by e and var, respectively. Following the application of BN, Eq. (6) applies the ReLU activation function. This activation function determines whether a given neuron is active or inactive.

$$\widetilde{l}^{(K)} = \frac{l^{(K)} - e\left[l^{(K)}\right]}{\sqrt{\mathrm{var}\left[l^{(K)}\right]}} \tag{5}$$

$$\mathrm{Re}\ LU\left(l\right)=\left\{\begin{array}{ll}0, & if l\le 0\\ l & otherwise\end{array}\right. \tag{6}$$

In (6), l is the input of the function, and its output is zero for negative numbers and l for positive numbers. The architectural diagram of Hybrid AlexNet-ShuffleNet model is illustrated in Fig. 3.

Let X_1 be the output obtained from AlexNet, which is $soft\max\left(y\right)_I$, and X_2 be the output gained from ShuffleNet.

Thus, the output from the merging layer is computed as,

$$X_3=\sum_d\sum_z S_{t+1}*X_2*W \tag{7}$$

where, W denotes the weight ranges from (0–1).

$$S_{t+1}=S_t+\frac{S_{t-1}}{2}+\frac{S_{t-2}}{3}+\cdots+\frac{S_{t-M}}{M} \tag{8}$$

where, M depends on the number of features, i.e. augmented images.

$$S_{t+1}=\sum_d\sum_z A_1\times W_1+\frac{1}{2}\sum_d\sum_z A_2\times W_2+\cdots+\frac{1}{M}\sum_d\sum_z A_M\times W_M;1<d\le N,1<z\le K \tag{9}$$

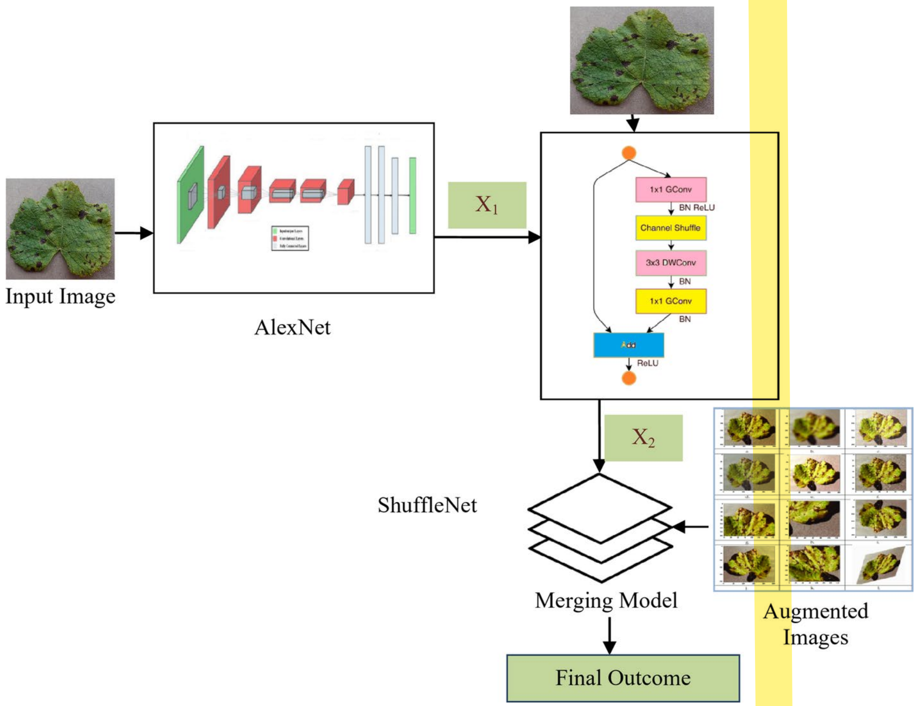


Fig. 3 Architectural diagram of Hybrid AlexNet-ShuffleNet model

where, $A_1, A_2, \ldots, A_r \ldots, A_M$ denotes the augmented images of dimension $N \times K$, $\times$ is the element wise multiplication and W_r denotes the weights in the range (0–1).

Once the healthy and unhealthy categories of the plant leaves are identified using the proposed AlexNet-ShuffleNet, the second stage of classification is done to categorize the unhealthy categories of the plant leaf diseases.

4 Algorithm-Hybrid AlexNet-ShuffleNet

1. Import the initialized factors (i.e., biases and weights in the filters) of AlexNet and ShuffleNet.
2. Feed the RoI extracted image to the convolution layer of the AlexNet, which passes through the layers of pooling, another set of convolution, max pooling, and at last to the fully connected layer. A residual image is produced at the output layer. The output function of the AlexNet network uses the ReLU, as in Eq. (2).
3. Feed the output image from the AlexNet and the RoI extracted image as the input to the convolution layer of ShuffleNet, which is transferred to the shuffleNet units.
4. Finally, the output from the ShuffleNet, together with the augmented image is fed to the Map layer that merges both the network outputs to get the vector enclosing the probability rate of every class prediction.
5. Calculate the cost function, which is usually the squared sum function.
6. The Adam optimizer is normallyenlisted to update the weight values of the respective filters to minimize the error,

$$w_t = w - a\left(\frac{m}{\sqrt{v}+\varepsilon}\frac{\sqrt{1-\rho_v}}{1-\rho_m}\right) \tag{10}$$

   where w_t is the weight to update, m represents the first-moment vector, v symbolizes the second and first-moment vector, α is the learning rate, ρ_m and ρ_v denotes the adaptive learning rate time decay factor.
7. Repeat steps 2 to 6 until the count of training reach the maximum.

5 Results

This segment presents the outcomes and analysis of the novel Hybrid AlexNet-ShuffleNet approach for detecting plant diseases. The implementation of this approach has been carried out in Python. The study have systematically presented the results in an organized manner using diverse visual aids like graphs, charts, and tables to ensure that the findings are presented in a comprehensive and easy-to-understand way.Table 1 demonstrates the parameters and its value.

Table 1 Parameters and its value

Parameters	Value
AlexNet	
Batch size	128
Epochs	100
Learning rate	0.01
Activation	Relu
Optimizer	Adam
Shuffle Net	
Batch size	32
Epochs	100
Learning rate	0.01
Activation	Soft max
Optimizer	Adam

5.1 Dataset description

The following segment illustrates the datasets performed to experiment in proposed Hybrid AlexNet-ShuffleNet model. Five datasets are used to conduct the experiment. The datasets were grape dataset [25], rice leaf dataset [26], sugarcane disease dataset [27], black gram plant leaf disease dataset [28] and dataset of tomato leaves [29].

Apple dataset [25] The Apple Disease Image Dataset is a collection of images of apple leaves affected by various diseases. It is a compilation of images and annotations for training and evaluating machine learning models for grape detection and counting. The images were captured using a mobile robot and feature a wide variety of grape varieties in different stages of maturation and under different lighting conditions. The apple dataset contains 4 classes, namely apple_scab, apple_blackrot, apple_cedar_apple_rust and apple_healthy. Each class contains 630, 321, 275, and 1645, respectively.

Rice leaf diseases dataset [26] To support research on rice leaf diseases, a dataset containing 120 high-quality JPEG images of diseased rice leaves is available. The images are arranged into three categories, according to the type of disease. Each class contains 40 images, providing ample data for developing machine learning models to accurately detect and classify rice leaf diseases. This dataset is an invaluable resource for researchers working to improve crop yields and food security, and to mitigate the impact of diseases on rice crops.

Sugarcane disease dataset [27] It is a compilation of images and annotations for developing and testing ML algorithms for sugarcane detection and counting. The dataset contains 3 classes, each classes contains 100 images each. Each image is annotated with bounding boxes around individual sugarcane plants, and the dataset includes information on the plant's height, width, and distance from other plants. The images were captured using drones and ground-based cameras, providing a diversity of perspectives and lighting conditions for training and testing ML techniques.

The blackgram plant leaf disease dataset [28] Consists of five categories, comprising 1000 images in total. The images depict the four most prevalent leaf disorder affecting Blackgram crops: a healthy category, Powdery Mildew, Yellow Mosaic, Leaf Crinkle, and Anthracnose. The dataset was sourced from agriculturefields located in Nagayalanka, Krishna (d.t), Andhra Pradesh, India. Additionally, each image contains bounding boxes around the leaf regions and has labels indicating the disease type and its severity.

Tomato Leaves Dataset [29] is comprised of two datasets, each containing images of tomato leaves from different sources. A total of 14,531 images are containing in the dataset, with each image featuring a single tomato leaf along with a corresponding background. The original images were combined, and unnecessary categories were deleted, with the image size being adjusted from 256 ×256 to 227 ×227. Five subsets of 5-fold cross-validation were created using this database. The first dataset includes images of tomato leaves featuring ten different categories, such as Two-spotted spider mite, Tomato yellow leaf curl virus, Healthy, Tomato mosaic virus, Leaf Mold, Target Spot, Septoria leaf spot, Late blight, Early blight, and Bacterial spot. The second dataset comprises images sourced from Taiwan, with six categories—five disease categories and one health. Each image in the second dataset may have a multiple leaves, single leaf, a complex background or a single background. The categories of the second dataset are Powdery mildew, Late blight, Black leaf mold, Healthy, Gray leaf spot, and Bacterial spot.

5.2 Experimental Results

Figure 4 displays the outcomes of the sample images. The original image is displayed in Fig. 4(a), followed by its rotated version in Fig. 4(b). Figure 4(c) showcases the sheared image, while a zoomed-in version of the image is illustrated in Fig. 4(d). The flipped image is presented in Fig. 4(e), and (f) shows an image that underwent a brightness adjustment. Finally, Fig. 4(g) displays the ROI image. By comparing these images, it is possible to identify the changes and variations in their visual properties. This analysis provides valuable insights into the technique's effectiveness in detecting changes in digital images. Figure 5 demonstrates the original image and segmented image.

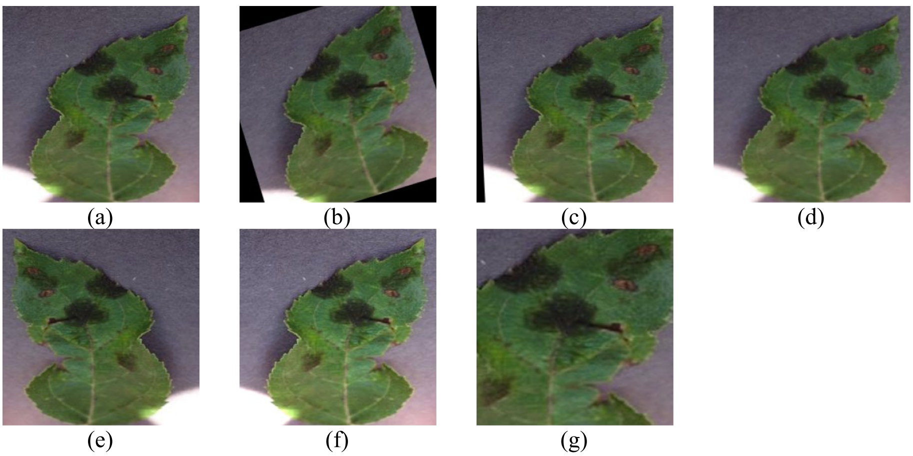


Fig. 4 Image results, **a** Original image, **b** Rotated Image, **c** Shear image, **d** Zoomed image, **e** Flipped image, **f** Brightness adjustment, **g** ROI image


(a)

(b)

Fig. 5 Image results, **a** Original image, **b** Segmented image

5.3 Performance metrics

In order to establish the efficacy of the Hybrid AlexNet-ShuffleNet approach, several performance metrics were utilized. These metrics are as follows:

a) **Accuracy:**This metric measures the accuracy of the Hybrid AlexNet-ShuffleNet model by determining the proportion of correct forecasts made. This is done by separating the entire amount of correct forecast from the entire amount of forecast made.
b) **Sensitivity:** Sensitivity calculates how effectively the Hybrid AlexNet-ShuffleNet technique recognizes positive cases. It is considered by separating the number of true positives (i.e. positive cases precisely acknowledged by the strategy) by the entirety amount of true positives.
c) **Specificity:** This metric assesses the ability of the Hybrid AlexNet-ShuffleNet technique to correctly identify negative cases. Specificity is measured by unscrambling the number of true negatives (i.e. cases accurately accredited as negative) by the total number of true negatives.
d) **RoC:** The Receiver Operating Characteristic (RoC) curve is a graphical demonstration that depicts the performance of a binary categorization approach across different categorization threshold levels. The TPR (True Positive Rate) is conspired beside the FPR (False Positive Rate) to produce the RoC curve.

5.4 Performance analysis

5.4.1 Varying training data

The presented Hybrid AlexNet-ShuffleNet strategy for its effectiveness in detecting plant disorder using assorted performance metrics, including specificity, accuracy, and sensitivity were evaluated. The performance examination is exemplified in Fig. 6. Figure 6(a), observed a significant increase in accuracy up to 0.9192 for iteration 100 when 80% of the training data was utilized. In comparison, the accuracy was 0.8996 for the same iteration when training data was limited to 60%. Figure 6(b) shows that the sensitivity of the presented technique was 0.979 at iteration 100 when 90% of the training data was utilized. On the other hand, for iteration 60 when 80% of the training data was utilized, the sensitivity of the presented Hybrid AlexNet-ShuffleNet technique was 0.910. Figure 6(c) displays the performance examination of specificity, which showed that the developed technique assimilated a specificity of 0.850 at iteration 40 when 70% of the training data was utilized. By employing these performance metrics, the study has demonstrated the effectiveness of the presented Hybrid AlexNet-ShuffleNet technique for plant disorder identification.

5.4.2 Varying K-fold

Figure 7 presents the performance evaluation of the developed technique using k-fold cross-validation, in terms of accuracy, sensitivity, and specificity. As shown in Fig. 6(a), the Hybrid AlexNet-ShuffleNet technique accomplished an accuracy of 0.950 for the 9 k-fold at the 100 th iteration, indicating its high accuracy in detecting plant diseases. Figure 7(b) illustrates the sensitivity analysis of the developed technique, revealing that the procedure achieved a sensitivity rate of 0.930 for the 7 k-fold at the 60 th iteration, which could effectively identify diseases in plants. In addition, Fig. 7(c) presents the specificity analysis of

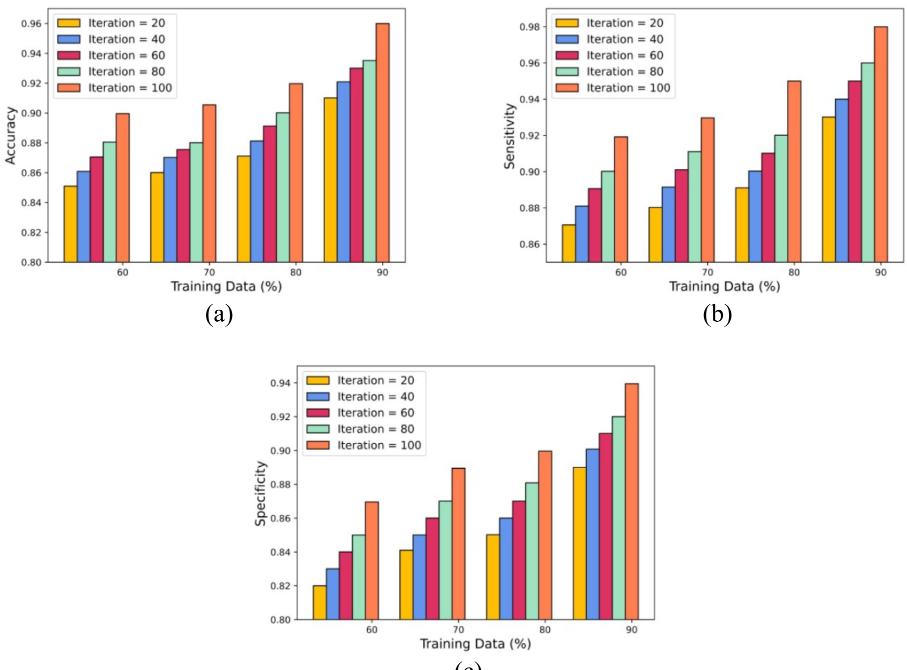


Fig. 6 Performance assessment of the presented AlexNet-ShuffleNet based on training data, **a** accuracy, **b** sensitivity, and **c** specificity

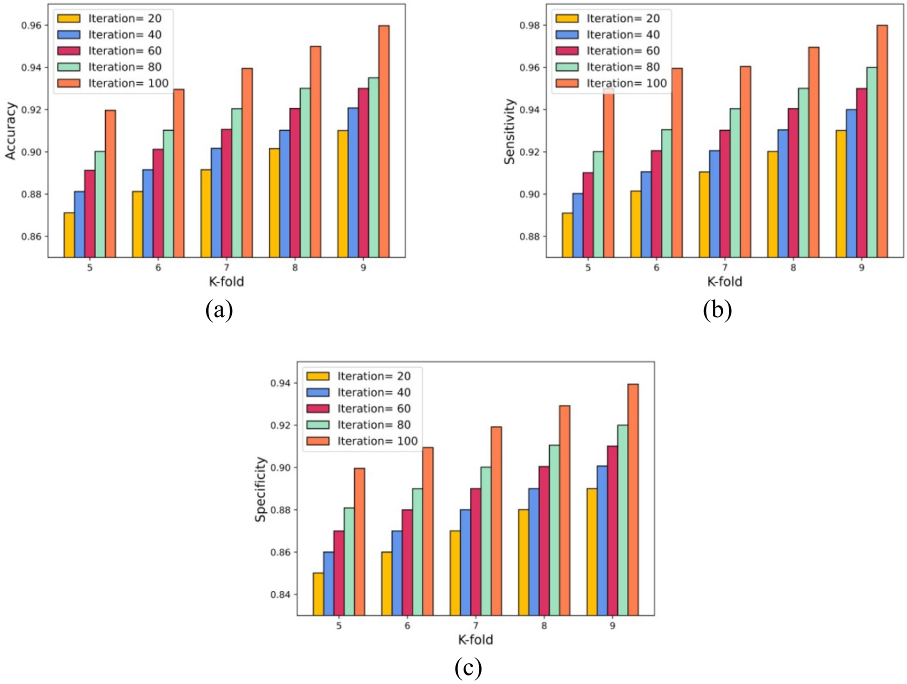


Fig. 7 Performance evaluation of the presented Hybrid AlexNet-SuffleNet strategy according to the K-fold, **a** accuracy **b** sensitivity **c** specificity

the presented AlexNet-ShuffleNet model, demonstrating that the strategy accomplished a specificity rate of 0.920 for the 7 k-fold at the 100 th iteration.

5.5 Comparative analysis

As part of this study compared the Hybrid AlexNet-SuffleNet method to other established models such as CNN (Vishnoi, et al., 2022), Improved Faster-RCNN *(Masood,* et al., *2023)*, and EfficientNetV2 (Sunil, et al., 2021). These models were considered in the context of the analysis.

5.5.1 Training data

In Fig. 8, a comparative evaluation of the developed strategy with different methods is presented. As shown in Fig. 8(a), different methods were evaluated based on their accuracy, and the proposed Hybrid AlexNet-ShuffleNet model achieved an accuracy of 0.8996 for the training data of 60%, which outperformed the CNN, Improved Faster-RCNN, and EfficientNetV2 models with their accuracy rates of 0.8594, 0.8694, and 0.8792. Figure 8(b) shows the comparative measurement for sensitivity, indicating that the Hybrid AlexNet-ShuffleNet method achieved a sensitivity rate of 0.9798 for the training data of 90%, whereas the CNN and Improved Faster-RCNN methods acquired sensitivity rates of 0.9305 and 0.9405. Henceforth, the comparative measurement in terms of specificity is presented in Fig. 8(c),

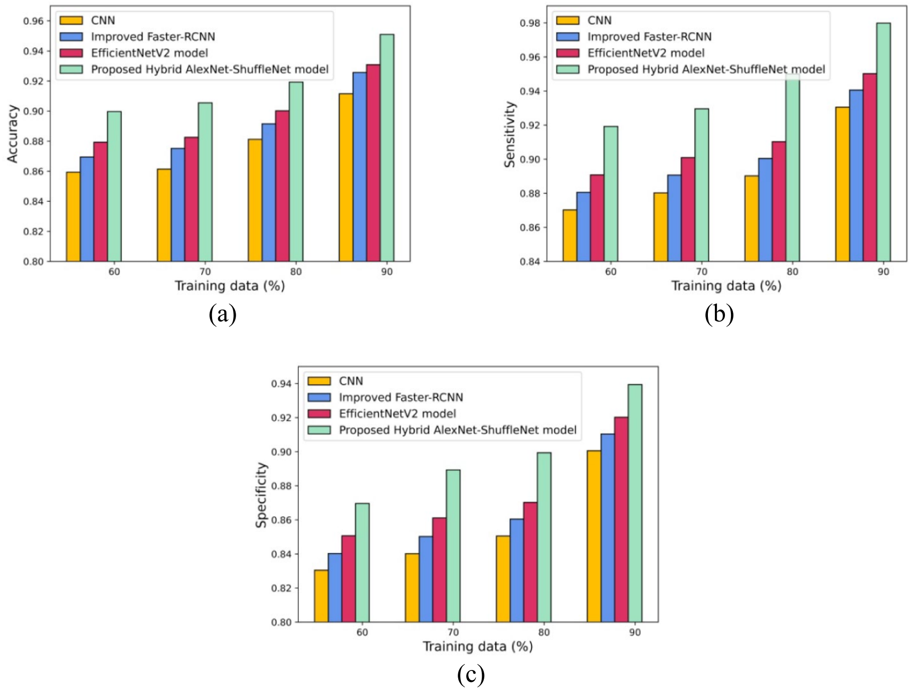


Fig. 8 Comparative measurement of the method according to training data **a** accuracy **b** sensitivity **c** specificity

demonstrating that the proposed Hybrid AlexNet-ShuffleNet method acquired a superior specificity rate of 0.8893 for the training data of 70%, outperforming the Improved Faster-RCNN and EfficientNetV2 methods with their specificity standards of 0.8502 and 0.8611.

5.5.2 K-fold

The efficiency of the presented Hybrid AlexNet-SuffleNet method is measured up to other traditional strategies in Fig. 9. The findings exemplify that the presented technique outperforms the CNN, Improved Faster-RCNN, and EfficientNetV2 approach in terms of sensitivity, specificity, and accuracy. Specifically, in Fig. 8(a), the developed procedure attained an accuracy score of 0.9291 for a k-fold of 6, which is higher than the scores of the other models. Figure 9(b) also indicates that the Hybrid AlexNet-SuffleNet strategy is effectual in terms of sensitivity, with 0.9596 for a k-fold of 7, compared to the sensitivity values of the CNN (0.9102) and Improved Faster-RCNN (0.9205) models. Furthermore, Fig. 9(c) shows that the presented technique accomplished the highest specificity value of 0.9392 for a k-fold of 9, while the CNN and EfficientNetV2 models received values of 0.9004 and 0.9201.

In Fig. 10, a visual depiction is given to showcase the analytic capabilities of binary classifiers. The evaluation includes the ROC curves of the Hybrid AlexNet-ShuffleNet technique proposed in this study, as well as that of traditional models such as CNN, Improved Faster-RCNN, and EfficientNetV2. The results demonstrate that the ROC curve of the

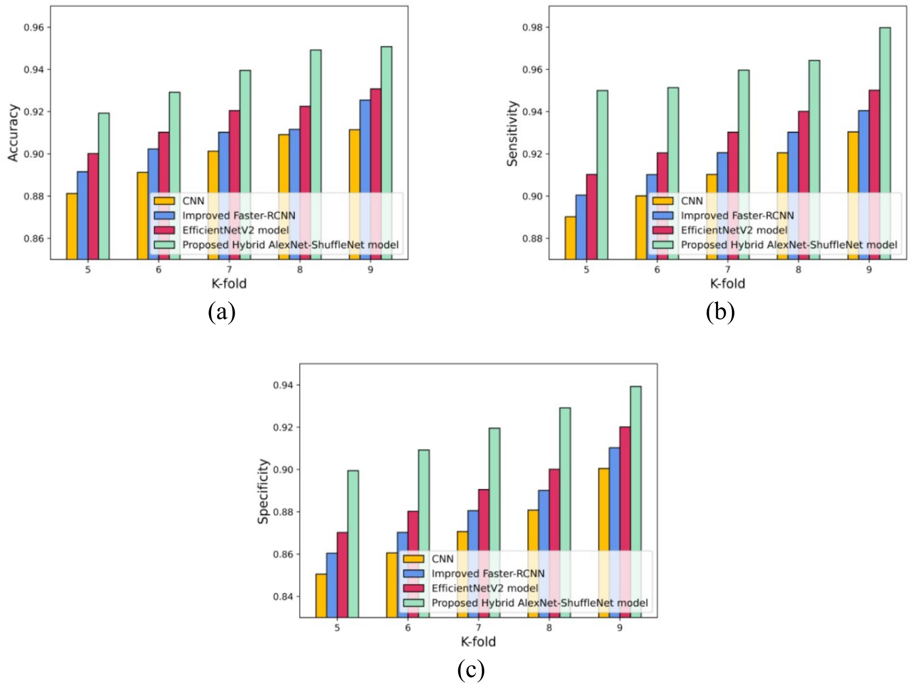
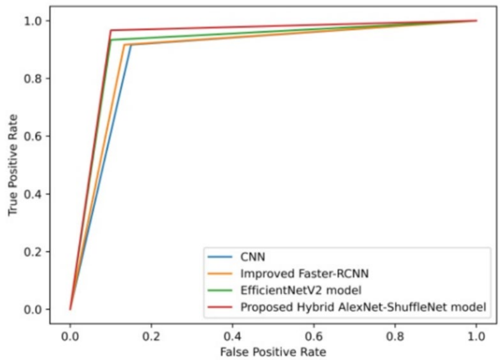


Fig. 9 Comparative measurement of the techniques according to k fold **a** accuracy **b** sensitivity **c** specificity

Fig. 10 Graphical depiction of ROC



newly introduced technique performs exceptionally well compared to conventional methods, as indicated by the superior TPR value for a given FPR. This finding serves as strong evidence to support the outstanding performance and effectiveness of the introduced Hybrid AlexNet-ShuffleNet strategy in binary classification.

Figure 11 illustrates the graphical depiction of training loss of proposed hybrid model. For iteration 100, the training loss of AlexNet was $8.86e^{-02}$ and training loss of ShuffleNet was $3.44e^{-01}$. Table 2 illustrates the comparative discussion of the developed Hybrid AlexNet-ShuffleNet model. The presented Hybrid AlexNet-ShuffleNet model acquired an accuracy

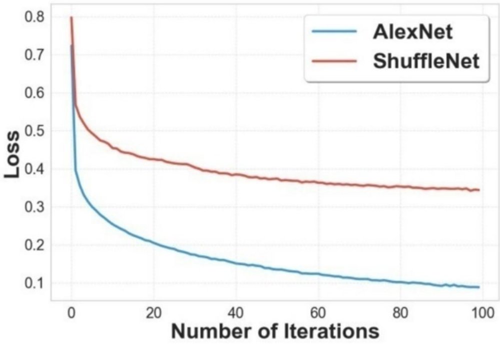


Fig. 11 Graphical depiction of training loss for proposed hybrid model

Table 2 Comparative discussion of the presented approach

Metrics	CNN	Improved Faster-RCNN	Efficient-NetV2 model	Proposed Hybrid AlexNet-ShuffleNet model
Accuracy	0.9115	0.9256	0.9308	**0.9509**
Sensitivity	0.9305	0.9405	0.9502	**0.9798**
Specificity	0.9005	0.9104	0.9202	**0.9393**

Table 3 Computational time

Methods	Time (sec)
CNN	439.313
Improved Faster-RCNN	278.198
EfficientNetV2 model	194.706
Proposed Hybrid AlexNet-ShuffleNet	**76.314**

of 3.77% when compared to CNN and also attained 2.66% accuracy when compared to the Improved Faster-RCNN model. The presented strategy attained a sensitivity of 3.02% when compared to the conventional model of the EfficientNetV2 model. When compared to the conventional model, CNN, the presented Hybrid AlexNet-ShuffleNet strategy attained a specificity of 4.13%. The results demonstrated that the Hybrid AlexNet-ShuffleNet model outperforms the current methods, suggesting its potential as a powerful method for enhancing sensitivity, specificity, and accuracy in classifying tasks. Table 3 demonstrates the computational time of the proposed and conventional models.

6 Conclusion and future scope

The study proposes a Hybrid AlexNet-ShuffleNet framework for plant leaf disorderidentification. The investigationaloutcomesprove that the presented hybrid approach outperforms both AlexNet and ShuffleNet in terms of specificity, accuracy and sensitivity. The model offers practical applicability for farmers and plant disease researchers to detect and prevent crop losses caused by plant leaf diseases. The hybrid model proposed in the study combines the advantages of both AlexNet and ShuffleNet, resulting in improved accuracy compared to the individual networks. AlexNet excels in learning high-level features, while ShuffleNet specializes in reducing the computational difficulty of deep neural networks. The hybrid technique leverages these strengths with the RoI extracted to enhance the overall performance of the procedure. The projectedschemereached maximum accuracy rate of 95.09%, sensitivity rate of 97.98% and specificity rate of 93.93%. Overall, the hybrid framework has the potential to be a valuable tool for agricultural production in the recognition and prevention of plant leaf disorder. As future work, the diseases identified can be classified further into bacterial, viral or fungal infections using transfer learning techniques. Moreover, the plant leaf disease classification process can be deployed in IoT platform.

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