Comparative Analysis of Neural Network Based Image Processing for Lung Malignant Tumour Diagnosis

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Abstract:
A biomedical imaging system requires timely disease identification in order to avoid major risks for critical care patients. In most cases, collecting a biopsy sample from the patient, staining, histopathology imaging, and decision-making by an expert physician take a long time. If the image processing unit is part of the imaging system, a timely decision can be made. For efficient decision-making on CNN models, which are more expensive, a large amount of memory and a high-speed processor are required. If proper models that require less memory and high speed are identified, those models can be utilised in an imaging system for decision-making. This paper focuses on lung malignant tumour diagnosis using pertained deep networks to identify the network's capability to work on low-speed and low-performance devices. Ten pre-trained networks were selected based on module size, number of layers, and depth. Three networks were identified based on their high performance with moderate size, layers, and depth and accuracy of more than 90%.

Keywords: Pre-trained networks, transfer learning, training, validation and testing, Lung Malignant,

1 Introduction:

Deep learning Pre-defined models are selected based on memory needed by the model, retention-based performance, and speed of prediction for a new image [1]. Pre-trained Deep learning can be a very simple approach to helping the farmer identify what kind of diseases the particular plants have left [2] [3]. Our research focuses on identifying the trained network that uses the least amount of memory, has a medium number of layers, and takes the least amount of time to predict on low-performance devices such as the Raspberry Pi, the Arduino Uno, and so on. Pre-trained network architectures of deep classifiers are used without visualization. Three learning techniques for lung cancer images on an image database were tested with specialists testing numerous best-in-class Convolutional Neural Network (CNN) architectures with saliency maps as a perception strategy [4] [5].

Each class image was trained using CNN networks. A big database was used to train CNN networks for feature learning, and training with a greater number of times higher accuracy can be achieved [6] [7]. The highlights computed by the primary layer are common and can be reused in totally different issue spaces, whereas the highlights computed by the final layer are particular and depend on the chosen dataset and errand [8] [9]. Layers closer to the inputs allude to common highlights, though the classifier portion and a few of the higher layers of the convolutional base allude to particular highlights [10] [11].

In our research work, ten CNN networks based on their size, input size, and layers are used. Based on our literature review, we identified that the majority of researchers focused on identifying the faster network with a high accuracy percentage with higher-end processing devices [12] [13]. Our study is to identify the performance of the pre-trained network with the minimum number of inputs required to train it to moderate accuracy [14] [15]. Identify a lightweight, pre-trained network that can be trained on low-processing-speed devices used for real-time agriculture monitoring and control, such as the Raspberry Pi, Arduino, MSP430, and so on [16] [17]. The study was performed using a pre-trained network available in MATLAB with a plant village image dataset [18] [19]. Available deep networks in MATLAB with their specifications are given in tables 3 and 4 with respect to their layers, depth, memory, parameters, and image size [20] [21].

Table 3 Specification of Deep learning model in MATLAB

Number of layers	Depth	Memory	Parameters in millions	Image specification
19-709	8 – 201	5.2MB – 535MB	1.24 – 144	(224,224) – (299,299)

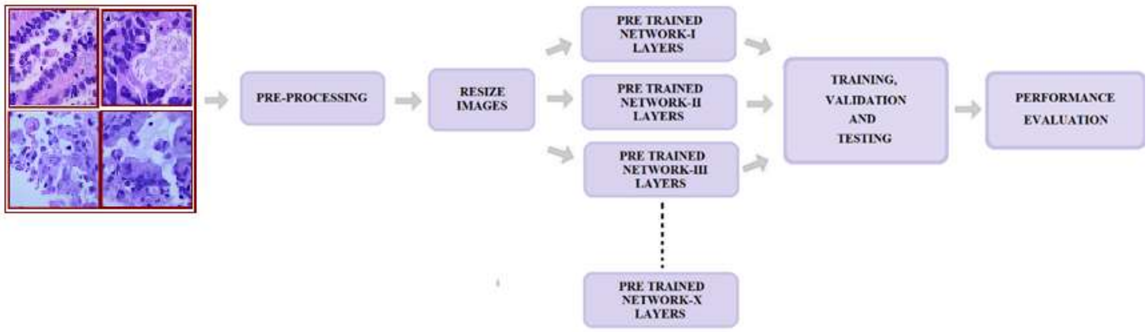
Table 4 Pre-trained network used with its specifications.

S. No	Module	Network	Layers	Module Size	Image Input size	depth
1	Network module-I	Squeezenet	68	5.2 MB	227-by-227	18
2	Network module-II	Googlenet	144	27 MB	224-by-224	22
3	Network module-III	Inceptionv3	316	89 MB	299-by-299	48
4	Network module-IV	Densenet201	709	77 MB	224-by-224	201
5	Network module-V	Mobilenetv2	155	13 MB	224-by-224	53
6	Network module-VI	Resnet18	72	44 MB	224-by-224	18
7	Network module-VII	Resnet50	177	96 MB	224-by-224	50
8	Network module-VIII	Resnet101	347	160 MB	224-by-224	101
9	Network module-IX	Alexnet	25	227 MB	227-by-227	8
10	Network module-X	Vgg16	41	515 MB	224-by-224	16

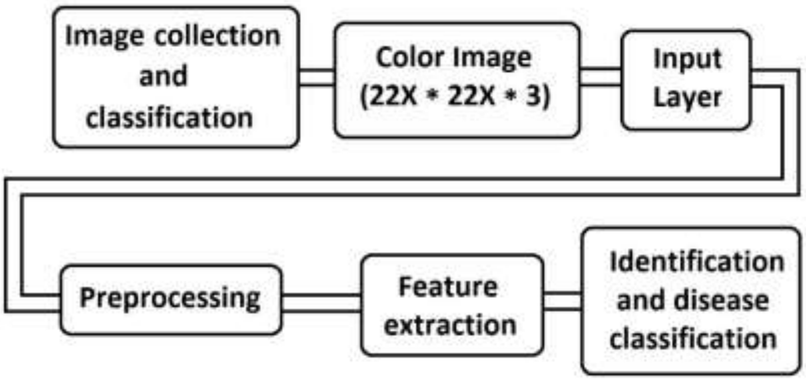
MATLAB included 19 deep networks that can be selected based on network type, depth, size, parameters, and image size (A. KP et al., 2021; Alex Krizhevsky et al., 2012). The term "depth" is described as the range of sequential convolutional or absolutely linked layers on a route with the input layer and the output layer (Hari Krishnan G et al., 2014). Google has a depth of 22, a model size of 27 MB, nearly 7 million parameters, and an input image size of (244, 244). Initially, plant images were processed using basic models like AlexNet, VGG-16, VGG-19, and GoogLeNet (C Szegedy et al., 2015; Brahimi M et al., 2018).

Materials and Methodologies

Input images are grouped into three categories: training databases, validation databases, and testing datasets [22] [23]. The work flow and general block diagram for the proposed study are shown in figures 1(a) and (b) [24] [25]. The experiment was carried out with various sets of input images of tomato plant diseases based on the number of images and the type of disease [26] [27]. During the first stage of identification, twenty images from four types of diseases were chosen. The images were allocated in a random or known ratio format of 0.75/0.25. First-level experiments were performed to filter the networks, which take less time with high efficiency during the identification of plant diseases. Alexnet: Convolution, polling, and activation layers are used to extract features like edges, blobs, and colours. Layers of deep learning networks are input layers, which get input colour images, 3D images, or any other featured images. Convolution or transposed convolution layers for 2D and 3D, a grouped convolution 2D layer, and a fully connected layer We use three classes of histopathological images from the public dataset Borkowski AA et al., 2019 on the Kaggle website for our research work. Table 5 shows the image usage for the proposed study.



(a)



(b)

Figure 1 (a) Generalized block diagram for image processing using deep networks and (b) Process flow for disease identification using MATLAB

Table 5 Lung Cancer Image Dataset - Histo-pathological Images (Borkowski AA et al., 2019)

Lung Diseases Classes	**Diseases Class Name allocated**	**Training**	**Validation**	**Testing**	**Total**
Benign Tissue	Class 1	750	250	100	1100
Adenocarcinoma	Class 2	750	250	100	1100
Squamous Cell Carcinoma	Class 3	750	250	100	1100
Total		**2250**	**750**	**300**	**3300**

Table 6 Accuracy and duration (in sec) for fixed and randomized inputs.

Model	**Fixed Input**		**Randomized Input**	
	Accuracy in %	**Time in sec**	**Accuracy in %**	**Time in sec**
Network module-I	10	52	10.00	53
Network module-II	55	110	58.33	104
Network module-III	51.67	331	53.33	337
Network module-IV	70	587	71.67	615
Network module-V	58.33	151	56.67	190
Network module-VI	55	91	48.33	91
Network module-VII	55	230	63.33	226
Network module-VIII	56.67	410	58.33	398

Network module-IX	60	54	52.50	55
Network module-X	60	687	50	705

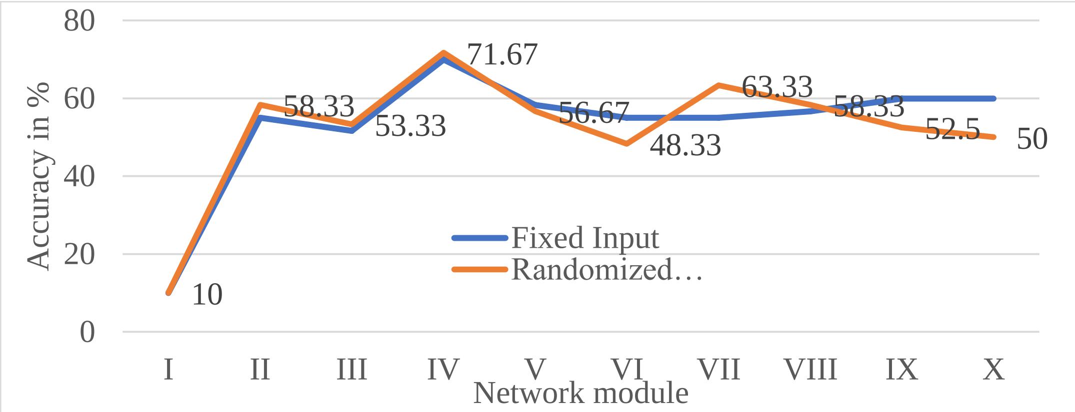


Figure 2 Fixed input vs randomized input impact on pre-trained networks

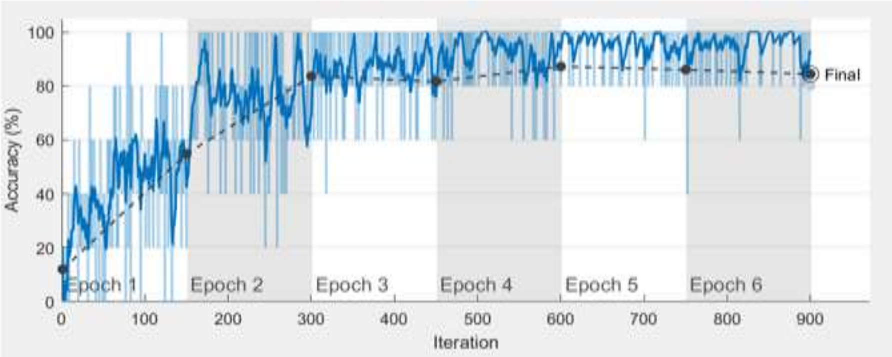
Experiments were performed using different numbers of input images. As a first stage for a lesser number of images for which a trained network can be able to give moderate accuracy within a lesser time, this was identified.

The input dataset was classified into six groups depending on the number of images: the first group had 20 images, the second group had 50 images, and similarly, other groups had 100, 200, 500, and 1000 images. Identified ten pre-trained networks based on the previous history, and their properties were trained, validated, and tested based on their accuracy. As a first stage, group one images were given as input to the identified ten networks one by one. Code was generated using the deep network designer tool in MATLAB with minimal layer modifications to display accuracy results as given in Table 6. Validation accuracy was tabulated for each network with different input image groups.

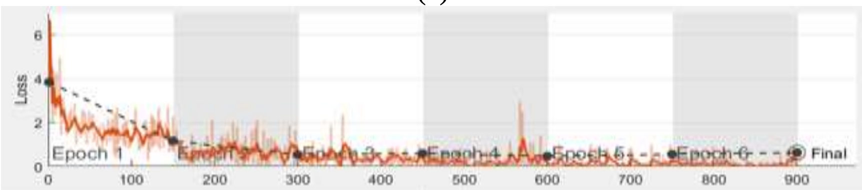
The accuracy values for each network module under study with fixed and random inputs are given in table 6. In the randomised input method, images are picked in a random manner from the given input dataset. The input selected for training and validation varies every time the programme is executed. The accuracy calculated was not constant in the randomised input method. The fixed input method was used for further experimental studies because the same images with a fixed number of inputs were given for training and validation for all ten networks under study. Figure 2 depicts the difference in accuracy between the fixed and randomised methods.

Results and Discussion

During the preliminary study, a fixed input method with uniform input for all pre-trained input was identified.The pre-trained network was trained with various inputs, including 20 input images in the first stage, 50 input images in the second stage, and 100, 200, 500, and 1000 input images in the third stage.The validation accuracy curve during training and validation is as shown in figures 3 (a) and (b). From table 7 and figure 4, it is observed that networks III, VII, VIII, and IX give more efficiency in less time and are minimum load pre-trained networks.



(a)



(b)

Figure 3 (a) and (b) Validation accuracy and loss curve for googleNet network with 500 images as input.

Table 7 Validation accuracy of pre-trained networks with different inputs

Module	Number of Input images					
	20	**50**	**100**	**200**	**500**	**1000**
Network module-I	10.00	11.11	15.22	17.23	35.34	40.32
Network module-II	58.33	79.56	84.40	89.12	97.56	99.87
Network module-III	53.33	83.56	87.57	90.23	97.78	99.78
Network module-IV	71.67	86.22	88.12	93.34	98.12	99.80
Network module-V	56.67	82.22	84.32	86.23	96.65	99.27
Network module-VI	48.33	76.00	83.72	85.91	95.60	97.35
Network module-VII	63.33	84.89	87.12	90.01	97.23	99.42
Network module-VIII	58.33	84.44	87.01	89.87	97.03	99.21
Network module-IX	52.50	82.22	85.00	88.91	96.21	99.40
Network module-X	50	76.30	82.21	85.32	94.23	99.12

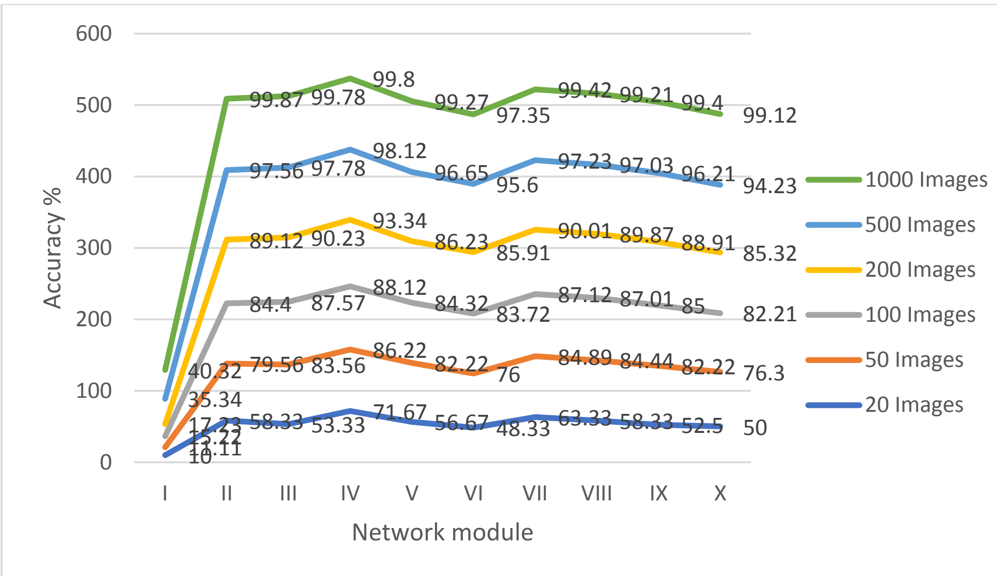


Figure 4 Training and validation input images impact on accuracy

Conclusions

Pre-trained networks Network III, Network VI, Network VII, and Network IX utilise less time to train the given set of input images with high accuracy. The identified networks can be used in lower-end processing devices for processing agricultural images to identify diseases in an economic way. Our experimental results clearly indicate the performance of a pre-trained network with a minimum number of layers, a smaller module size, and a medium depth showing comparatively high accuracy. Economically weak countries with agriculture as their backbone can utilise the advancement in the neural network. Real-time plant diseases in agriculture can be diagnosed using drones with medium-low processing speeds and memory devices like the Raspberry Pi, Arduino, and MSP430. These devices can utilise the identified networks.

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Conflict of interest

The seven authors of this paper have no conflict of interest in any means.

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