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Automatic Trees Density Classification Using Deep Learning of Unmanned Aerial Vehicles Images

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Abstract: Remote sensing (RS), represented by Unmanned aerial vehicles (UAVs) or Drones technology, has been an evolution of efficient solutions for smart applications in our world. Remote sensing from unmanned aerial vehicles (UAVs) is used as a tool to improve intelligent agriculture. Combining deep learning (DL) based on a convolution neural network (CNN) with drone image data is a new technology for the classification of multiple vegetation densities. This paper presented a deep (CNN) neural network algorithm to classify three types of density for forest trees (high, medium, and low). The dataset (aerial imagery) collected by drone was for the Mosul woodland region (north of Iraq). The dataset contains different densities for tree distribution in the forest, as well as different locations. This is a modern method for environmental management that replaces the visual counting method. An automatic plant density classification is presented using aerial imagery with a dimensional of (128 ×128) pixels processed using open-source resources and a Python application (Keras, TensorFlow). The analysis is based on a DCNN algorithm to (VGG19) and (ResNet50) neural network the implementation on the aerial image. The accuracy achieved (84.07%) and (91.17%) respectively The study aims at managing the environment at the least cost and the best possible accuracy.

1. Introduction

Unmanned aerial vehicles (UAVs) or drones are a rising technology with a lot of potential for providing diverse and efficient solutions in real-world smart applications. As the need for civilian unmanned aerial vehicles (UAVs) grows,[1] as result, the usage of civilian drones must be integrated into our daily life. UAVs are an example of an emerging technology that addresses a wide range of application needs because of flexibility. The most prevalent method is the manual measurement; however, cost and manpower are important determinants for higher precision and for covering larger regions. In this article, digital approaches such as (UAVs), artificial intelligence, and digital image processing are investigated means that are used for this challenge. The use of UAVs in investigating the agricultural properties has been growing exponentially, with a greater focus on plant images. In this application, the UAV flies over a predetermined area of the farm and then, the visual computing system brings a vital part of the desired information. Remote sensing by unmanned aircraft is one of the necessities in management decisions in precision agriculture[2]. Unmanned aerial vehicles (UAV) technology produces images with a high resolution, and the user can determine the resolution of the image on which the drones are dependent. The detection of vegetation cover is one of the most important applications of UAVs. According to FAO reports that the loss of forest and vegetation cover makes biological diversity dwindle[3], DL varies from ML and this adds more "depth" (complexity) to the model. Feature learning, or the automatic extraction of features, which is an advantage of the deep learning characteristics of the higher levels of the hierarchy, are extracted from the raw data [4]**.** The DL architecture is a powerful artificial neural network (ANN) architecture that gives the best results in the intelligent agriculture applications. The ganglion is a replica of the human neurons implemented by the functional units, which are related to the weight in order to classify or identified the objects. ANN is a mathematical model of neurons that are similar to the cells of the human brain. The most crucial functions of a neural network are training and learning. Artificial intelligence-based deep learning techniques are increasingly used in remote sensing applications. These strategies result in significant gains in a variety of fields and they provoke the interest of both academic and industrial communities [5]. Data obtained from the (UAVs) cameras has recently been used to assist the environmental management. Plants are mapped in high-resolution photographs using a variety of sensing methods, including UAV-based RGB, multi-hyperspectral cameras, Light Detection and Ranging (LiDAR), Synthetic and aerial photography. Despite their high performance in plant recognition, sensors like LiDAR and SAR are expensive[6]**.** Due to the low cost, availability in market, low risk and quick solution, UAV remote sensing technology has been widely utilized to detect plant density based on the ground point, classify plants using drones images and assess the color (RGB) using a deep learning model [7]. Several studies have been conducted to detect the density of plants such as potatoes, corn and other plants utilizing the aerial images of unmanned aerial vehicles based on the ground point using convolutional neural network methods, Faster RCNN and YOLO. Each one of these models performed well in terms of high-resolution images taken from low altitude [7][8][9]. Amongst the CNN well known and advanced networks are VGGNet, GoogLeNet and ResNet, which are classification networks. Other networks such as DetectNet, YOLO misdetection networks and FCN, SegNet, and U-Net are segmentation networks [10]. PointNet++, the 3D deep neural network (DNN) was used to classify numerous tree species (pine, birch and alder) in addition to the standing dead trees with crowns [11]. Th**e** distributio**n** of vegetation cover in forests is influenced by several factors, which do exist in the forest environment. The use of unmanned aerial vehicles (UAVs) to detect vegetation cover enables a rapid collection of separate data and making traditional forest inventory more efficient. The location and number of failures are critical for precise management of new afforestation, particularly during the replantation the seedlings in young forests [12]. Deep convolutional neural networks are used along with the Remote Sensing (RS) to classify the objects [13].

2.Background

The main DL architecture for image classification is the Convolutional Neural Networks (CNN). The basic CNN is made up of a series of convolutional layers, activation functions and pooling layers. The convolutional layer is the primary layer in the CNN that performs the convolution (i.e., element-wise dot product) between input data values and the kernel. The result is passed through the activation function, which performs a non-linear operation. The features are then passed through the pooling layers for down sampling to reduce the computational complexity. Finally, at least, one fully connected layer is used to provide the features map, followed by the softmax layer, which classifies the images based on probability values Various CNN architectures were developed over the years, beginning with LeNet (Lecun et al., 1999)[14][15].

2.2. Transfer learning based on CNN

Creating a new CNN network necessitates performing any type of task on which the network architecture is dependent, as well as training the network from the start, which takes a long time to achieve a good level [15]. If there is insufficient data, pre-trained networks i.e. VGG and ResNet can be used, which are the most commonly used in transfer learning [16]. VGG19 is a convolution neural network model that consists of 19 layers. VGG (Visual Geometry Group) is used to extract features. In this network, large size kernels are replaced with a large number of 3x3 filters, which allows to extract complex features at a low cost[17], ResNet50 is one of the deep learning networks and the most important, It involves 50 layers which is used detect and classify objects[18], and it is known as the network of high-speed roads through which information is entered to be passed directly to the next layer. This is regarded as a solution to the problem of weight deterioration in deep networks because weights invariance provides the highest accuracy.

3. Remote Sensing(RS) From Drone

3.1. Remote Sensing(RS) and artificial intelligence (AI) in digital agriculture:

Despite the fact that unmanned aerial vehicles (UAV) are used in a variety of applications, they are subject to technical and legal constraints such as power, speed, and flight path planning. Several studies have been conducted to address the issues associated with UAVs. Although drones is considered an eye in the sky, interpreting the data acquired is a challenge[19]. The most essential decision-making solution for environmental management and sustainable agriculture is the integration of modern Remote Sensing (RS) technology and Artificial Intelligence (AI) techniques and using them in the agricultural area. The DJI drone was used in all the imaging missions. The image dataset presented in this work is a directory of images of a drone equipped with a CMOS camera (Mavic ari2). Fig (1) shows a series of compact quadcopters produced by the Chinese technology company (DJI) for personal and commercial aerial photography purposes.

Fig-1:UAV(Mavic ari2)

Due to its low cost, the Mavic drone was utilized in this study and the aerial survey was conducted using this drone with a sensor (Effective Pixels: 12 MP and 48 MP) and the task was implemented using the application (DJI Fly), which is a (free program) on the mobile (smart) phone. Good contrast of resolution is a desirable feature of the drone photos. The photographs captured by these drones involve large areas. Geographical and temporal resolution can be obtained in time. A historical series of remote sensing data is available, which gives useful information on spatiotemporal variability. Images of vegetation that is exposed to mutations that might be caused by humans such as deforestation or that is exposed to diseases were obtained from the drone after choosing an appropriate flight plan in terms of the altitude, calibration prior to the flight and providing presentations on image analysis to ensure that the image is good and accurate. Agricultural research has pivoted on establishing long-term forest management techniques for decades. We must improve the resource usage efficiency of agricultural systems to meet current and future needs. Continuous technical advancements offer to solve the difficulties that will face humanity in the future decades [20].

3.3-Aerial photography

Aerial photography is one of the most promising way for performing phytosanitary crop monitoring. The process of photographing the earth's surface from airplanes, helicopters and other aircraft is known as the aerial photography. The advantage of using aerial photography for agricultural lands means efficiency because the period between photographing and getting the images is relatively short compared to the time in which satellite photographs are received.

4. Methodology:

4.1. Experimental stages: The proposed technique of the work of this research can be described in the following steps: (i) Using remote sensing to capture photographs from unmanned aerial vehicle (UAV) camera in the field to create a dataset. (ii) Data augmentation: Due to the huge dataset required, different data manipulations such as cropping, illumination and rotation to avoid over-fitting. (iii) Developing a deep learning neural network model based on a convolutional neural network (CNN) to identify and classify different trees densities (high, low and moderate). (iv) The data was split into training and testing sets and then the deep learning model (CNN) was trained on the data set. (v) Then the proposed deep learning neural network (CNN) model's performance in detecting tree density (high, low, and moderate) was assessed.

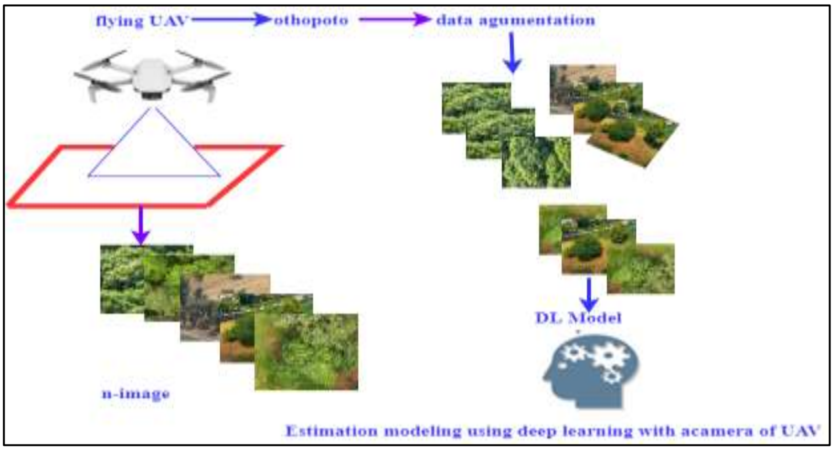


Fig-2: work methodology

4.2. Training dataset

The design of the training data set is critical for a better performance of CNN model. For the training dataset, (120 ×120)-pixel images are identified for different tree densities; the dataset collected from the drone was divided into (high, low, and medium) intensity levels. The training dataset is divided into training data, validation data and testing data. All the training data have the same dimensions. Moreover, the training dataset should contain a corresponding number of images for each section; otherwise, data augmentation is required. This includes several operations that are carried out to focus on the target to be extracted from the images.

Fig3: Sampling the dataset of different tree densities (high, low and medium)

5. Researcher's study and Results

The manual control device captures high-resolution photographs by means of the unmanned vehicle.

Fig4: Study aerial

(Adobe Lightroom) Commercial software was used to process the images. The technique was utilized to improve the interior and exterior qualities of the images that were obtained. The feature map was extracted from a**(** 128× 128 **)** RGB input image using a Deep CNN created by adding two fully connected layers to transfer learning network based on the VGG19 and ResNet50 as a feature extractor. The CNN presented was implemented in Python for training and testing. Adam was used as an optimizer. On an NVIDIA GPU, a CNN was implemented through an open- source program (Python language and using Keras-TensorFlow). A pre-trained network based on CNN that is VGG19 and ResNet50 was used. First, the VGG19 model was applied, and there were 3 layers in the proposed architecture with a 3x3 scale filter, Max pooling was used for feature map in each patch, a stride of 2, the max-pooling was set to 2x2 and then the fully connected layers with ReLU activation functions weights were used to produce the best results after 100 epochs on the dataset and a series of deep learning experiments were carried out. In the beginning, the CNN with 100 epochs and 112 images as input dataset for all density types (high, low, and mid) was trained. When several experiments were executed to the input datasets (150,1189 and 1503) on the CNN neural network to achieve the best accuracy, the outcome was dissimilar. The input dataset (1503) had an accuracy of 84.07% percent. Retraining by means of the VGG19 Network model mentioned earlier was unsuccessful in the current case. The training results were in accordance with a variety of datasets, as shown in Table No (1). The confusion matrix for VGG19, generated by training the network for each dataset, is shown in Fig (5). ResNet50[17] the network model was also mentioned earlier also. ResNet is a deep learning neural network that is used for image classification. The weight stabilization function has been used to ensure that the datasets produce the best results and do not take the random weight as the checkpoint does. The open-source program refers to the pre-trained model and the fully connected layers. After 100 epochs and a total number of input datasets of (1503), the best result was obtained with an accuracy of 91.17percent. Table. 2 displays the training results on a variety of datasets. The confusion matrix for ResNet50 generated by training the network on each data set is shown in Figure. (6) Accuracy is calculated from equation(Eq.1)

Accuracy (%)=$correctly\ predicted\ class\ total\ testing\ clas/total\ testing\ class$*100

$$\textbf{Accuracy(\%)}=\frac{TP+TN}{TP+FP+FN+TN}100\% \quad \textbf{(1)}$$

Table-1 of implementation experiences of vgg19	
Total number of image(dataset)	Accuracy of vgg19
112	75 %
150	65.2%
1188	78.21%
1503	84.07%

Where (TP)True Positive: is the number of the correct predictions for a specific class. (TN)True Negative: is the number of the correct predictions for a particular class, but they originally belong to another class. (FP)False Positive: is the number of the incorrect predictions for a particular class, but they originally belong to another class. (FN)False Negative: is the missing object for the class.

Table-2 of implementation experiences of ResNet50	
Total number of Images (dataset)	AccurayResNet50
112	82.35%
150	86.9%
1188	88.8%
1503	91.17%

5.1 Metrics for classification results*:*

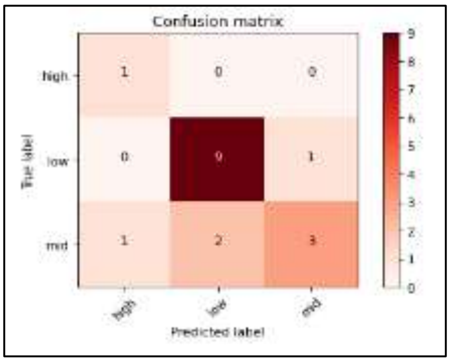
The performance of the model is measured using simple statistics such as false and true positive/negative classification ratios. So, the focus is on the percentage of output map pixels that are classified to (True positive) and (False Positive). These metrics are more specific.

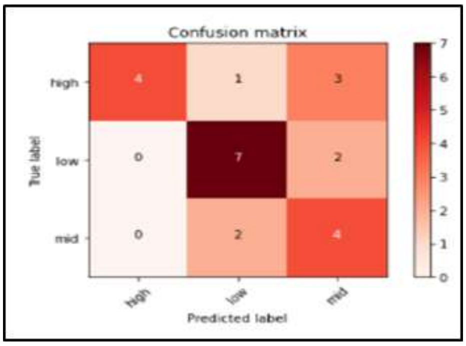
$$\textbf{Recall=} \quad \frac{TP}{TP+FN} \qquad (\mathbf{2})$$

Recall**:** It indicates the percentage of true positives that the model classifies correctly and sensitivity is another name for it.

$$\textbf{Precision} = \frac{TP}{TP+FP} \qquad (3)$$

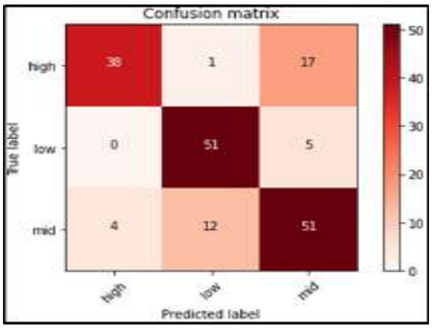
precision indicattissuestes the proportion of true positives to the total anticipated positives**.**

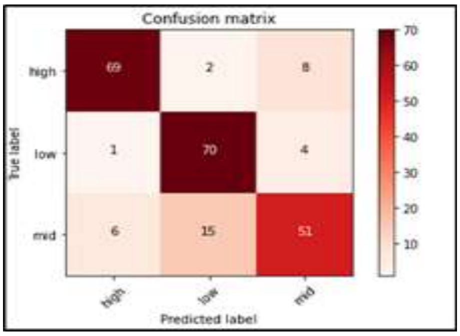




a:number image(dataset) 112

b:number of image(dataset) 150

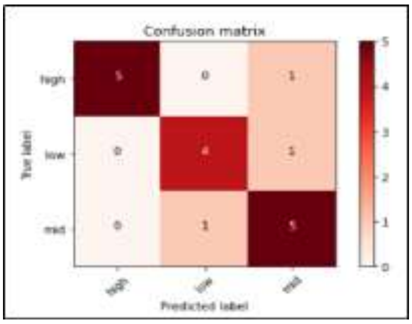


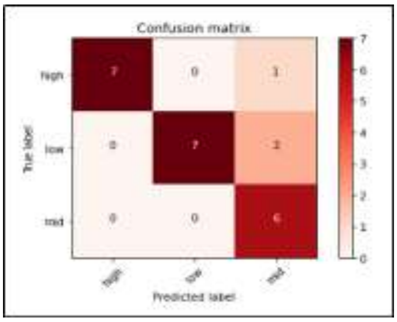


C: number of image(dataset)1188

d: number of image(dataset)1503

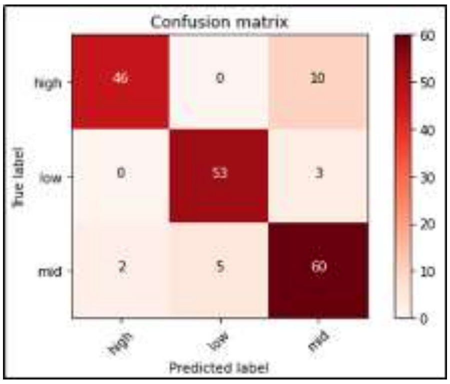
Fig-5 confusion matrices on the test dataset using (VGG19) network dataset input-112(b): dataset input-150(c):dataset input-1188(d):datasetinput-1503

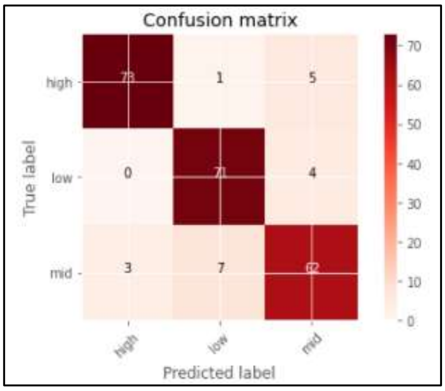




a:number of image(dataset) 112

b:number of image(dataset) 150





C: number of image(dataset)1188

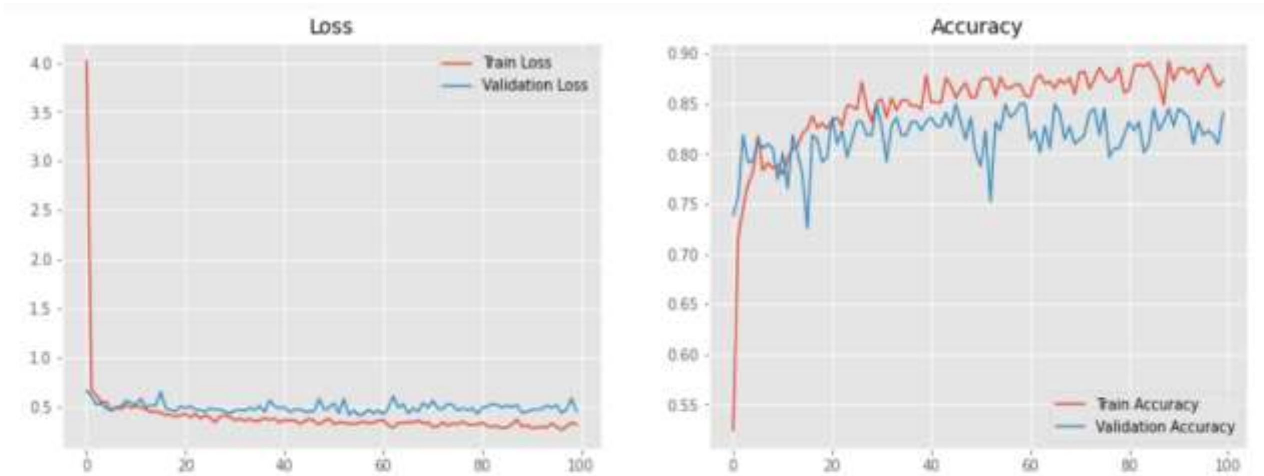
d: number of image(dataset)1503

Fig-6: confusion matrices on the test dataset using (ResNet50) network(a)dataset input-112(b):dataset input-150(c):dataset input-1188(d):datasetinput-1503

The result of total dataset is (1503) images for VGG19 and ResNet50 neural networks, as shown below in Table 3.

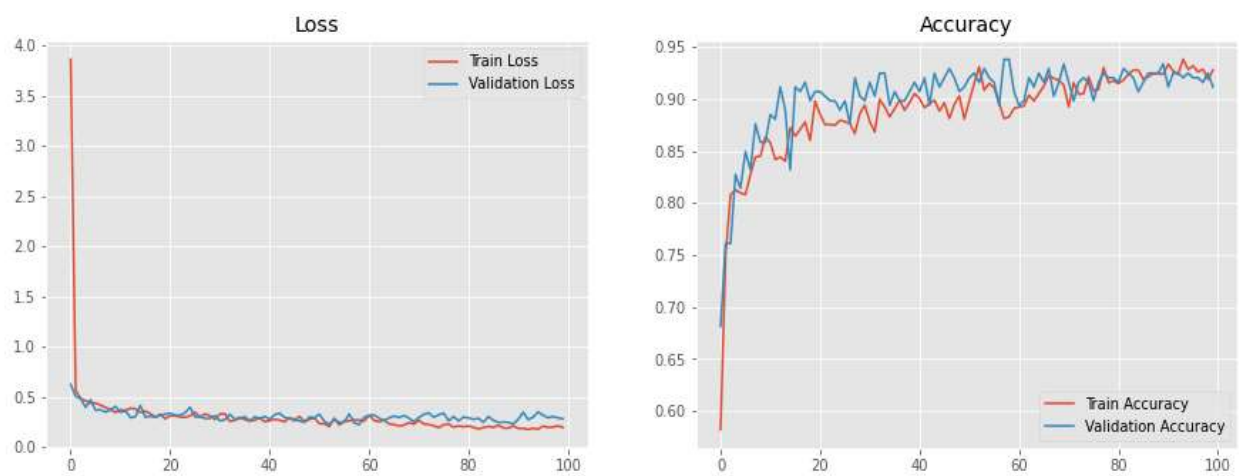
Table-3Trees densities detection using a model of CNN neural network

Model of CNN neural network	Classes of plant density	TP	FP	FN	Precision(%)	Recall(%)
VGG19	high	69	7	10	90	87.3
	low	70	17	5	80	93.3
	mid	51	12	12	80	70
ResNet50	high	73	3	6	96	92.4
	low	71	8	4	95.5	94.6
	mid	62	9	10	87.3	86.1



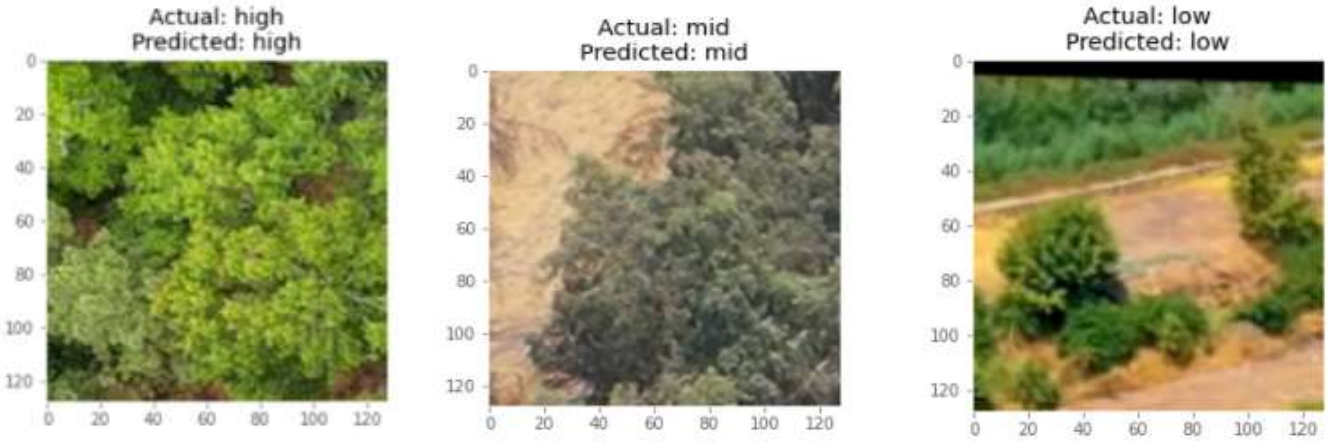
Epoch Epoch

Fig-7 Result of presented VGG19 network(a): traning loss(b):validation loss

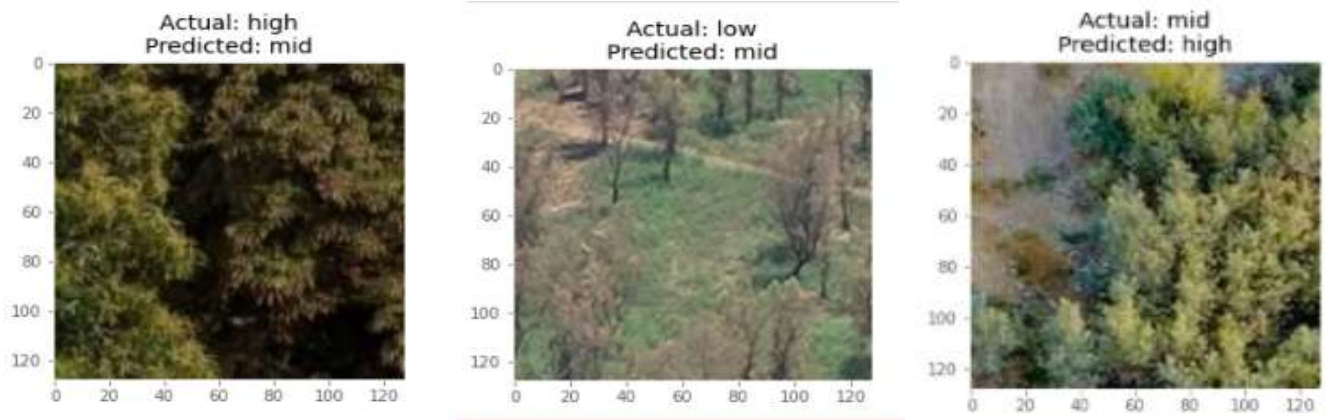


Epoch Epoch

Fig-8: Result of presented ResNet50network(a): traning loss(b): validation loss



a**: True detection of presented ResNet50**



b: false detection of presented ResNet50

Fig-9: detection of presented ResNet50(a) and (b)

6. Implications of research

The methodology proposed in this paper can provide fast and reliable information about the distribution of tree density in the forests, making it a useful tool for forest management practices. This study addresses the issue of inaccessibility in part. Because the technique is based solely on images, it can be used for forestry classification/management, and this results in more focused field surveys. for reforestation forests.

To create a comprehensive service platform, should be a Combination between DL algorithms and the current technology such as remote sensing from space is essential. The future growth of DL technology is still full of chances and challenges and it is characterized by a promising future.

7. Conclusion

A deep learning-based convolutional neural network can essentially deal with images and the aerial images captured by an unmanned aircraft were used in this study. Each image was sampled with a size of 128 x128 pixels. Moreover, the images were classified into three levels of intensity; low, medium and high. a series of tests to train the network to produce the best possible results were conducted. When the number of input images was low (112), the accuracy was low too, but when the number of images increased (1503), the accuracy improved accordingly. This demonstrates that the (CNN) network requires more data to be entered to achieve a high accuracy rate. A convolutional pre-trained networks was used (VGG19) and (Resnet50) for the same dataset were used. The accuracy of VGG19 was (84.07%), while ResNet50 was (91.17%). The ResNet50 convolution neural network was found to be the most accurate. This research is intended to be expanded by means of obtaining a larger dataset, more training epochs and an optimal training results that can be utilized to make environmental management decisions on the basis of the vegetation cover.

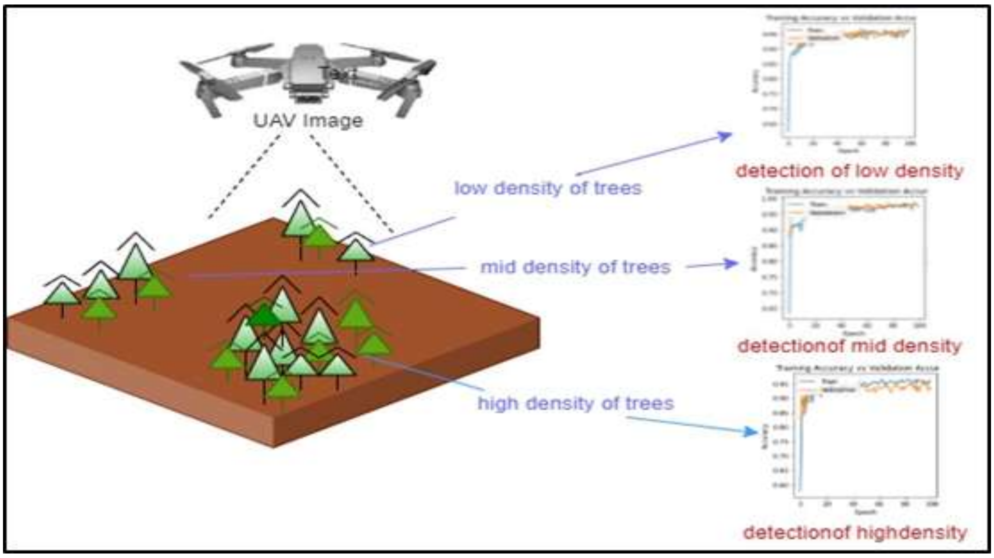


Fig-10: diagram classification of trees density from imaging drone and CNN model

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