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DESIGN OF A DEEP NETWORK MODEL FOR VEGETATION MONITORING AND CLASSIFICATION USING LEARNING APPROACHES

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Abstract – Monitoring natural vegetation (any plants) from remote locations is a significant factor that leads to a considerable challenge in the cultivation environment. Appropriate seasonal monitoring is essential to attain sustainable growth for providing a healthy environment for the farmers. Modern and advanced sensors have recently achieved natural vegetation monitoring using the Intelligent Monitoring System (IMS) using the Unmanned Aerial Vehicle (UAV) technologies. This research work aims to attain actual results by analyzing the factors that influence plant growth. The available sensors monitor the water level, agricultural system, pollution, and air quality and give it to the IMS for further analysis. Here, Layered CNN (L-CNN) with pre-trained U-Net architecture is used to classify the incoming data and analyze the factors that impact the farmers during the vegetation process. The UAV based vegetation monitoring systems genuinely consider the intelligent monitoring system. At last, an enhanced monitoring system with a robust outcome was designed to adopt de-noising approaches and develop an appropriate standard to assist in cultivation.

Keywords- Natural vegetation, remote location, intelligent monitoring system, UAV, layered CNN model.

1. Introduction

The most guaranteed result to bridge the gap between botanical taxonomies is the automatic identification of plant images. It gains the concerned attraction in the community of computers and botany. Various machine learning and deep learning models were suggested for identifying the natural growth of plant automatically. Millions of plant photos were obtained with the widespread emergence of Pl@ntNet mobile app [1]. In the real world, the mobile-based automatic identification of plants is necessary for formal-based ecological surveillance [2], exotic plant monitoring [3], environmental science, etc. The models of mobile-based plant identification have enhanced performance to attain higher attraction from engineers and scholars. There are many efforts to extract the leaf, fruit or flowers' local characteristics in today's world. Many authors utilize the variants on the characteristics of leaves to study the plants as a comparative tool. Few datasets related to a leaf have the Swedish leaf dataset, a dataset of Flavia, and a dataset associated with ICL is considered as the standard benchmark. Some characteristics like leaf shape and moment attributes are extracted from 15 Swedish tree classes and analyzed by Maggiori et al. in [4] using neural network (NN) with backpropagation. The local parameters are chosen by Huang et al. in [5] to describe extra veins pixels' features. The artificial neural network segments the veins and other leaves. The neural network shows efficiency in identifying plant vein images for effective feature extraction and the analysis is made by Wagner et al. [6]. This model attains the satisfying outcomes during leaf segmentation. The probabilistic NN is used as the classifier in finding the images of plant leaves that contain better accuracy in identification by Goeau than the BPNN [7]. The recognition of the natural leaf concept was suggested in 2013, and contour segmentation with the polygon leaf model algorithm was utilized to obtain the contour image [8]. The author attains texture features with the integration of leaf shape characteristics and other external features using the deep NN [9] concept. The proposed deep learning attracts the attention of researchers in the image recognition field. The deep learning system was designed by Angermueller et al. that had eight layers of CNN to find the images of leaves and obtain a higher rate of recognition. Few authors concentrate on the flower. The bag of visual word method was anticipated by Angermueller et al. to describe the shape, colour, texture, and so on. [10]. Harr features are combined with SIFT of the image and coded by Angermueller et al. [11]. The coding and the k-nearest neighbour technique is used for classification purpose. The prediction of picking the rose method was proposed in [12] with the integration of the BPNN. This study is generally infrequent. The multi-feature integration method was proposed by Li et al. with the help of Ainet preference [13]. Mobile applications like Pl@ntNet [1], LeafSnap [14], and Microsoft Garage's Flower Recognition **a**pps are dedicated to conveniently find the plants after continuous exploration on plant recognition technology.

Some models are even farther from the requirements of fully automated ecological surveillance on the automated plant taxonomy, which has good results. It can vary tremendously in cameras, contributors, time duration of the year, individual plant, etc. The conventional classification methods lie in the pre-processing step to avoid the complicated background and increase the needed features [15]. Handcraft feature engineering cannot deal with the larger datasets with unconstrained images. However, this work concentrates on modelling and efficient Layered CNN with a pre-trained U-Net model to deal with these issues. The BJFU100 dataset is acquired using the mobile phone naturally to overcome the difficulties mentioned earlier, and deep learning helps to breakthrough in recognition of the image. 10,000 images of plant species are available in the proposed dataset in the Beijing Forestry University campus, the design of building blocks is available in the 26-layer DL model which helps in identifying the non-familiar plant. The prediction rate attains 91.78%, which was achieved on the BJFU100 dataset in the proposed system. The proposed model helps in classification with reduced over-fitting issues. The simulation with MATLAB 2018a and the anticipated model shows a better trade-off than prevailing models. The work was organized as follows: In section 2, an extensive analysis of various existing approaches was performed, and the advantages and disadvantages were discussed. The purpose was to draft the research model to handle the issues. In section 3, the anticipated layered CNN with the U-net model was concerned with the classification process. The numerical outcomes and the corresponding discussions were provided in section 4. Finally, in section 5, the conclusion of the work with future research enhancements were discussed.

2. Related works

The well-being of humans relies on providing wide variety of ecosystem services is called Terrestrial vegetation. These services are provided to society on MEA, 2005, which forms the backbone of United Nations' Sustainable Development Goals. Moreover, vegetation changes dynamically, and it is not static and responds to drivers during climate changes as demonstrated by Sudre et al. [16]. Then the future trajectories are predicted for the vegetation dynamics is exceptionally suitable for the society and decision-makers. The analysis with natural vegetation is a critical task which is difficult to address the ecosystem dynamics over the large spatial extent. Phadikar et al. [17] presented the fundamental problems related to the environment, like loss in biodiversity and climate change, which are concerned globally, and policy responses are required by addressing them from the national level to the global level. Subsequently, the mismatch has happened between the critical relevance of ecological processes in the content such as uptaking the carbon vegetation, co-existence of species that are pertained from leaf to plant, and the information demands extend to a larger scale for the dynamic decision-making in the future. For decades, scaling has been the main problem in ecology, provided by Lee et al. [18]. It is methodologically difficult, which has increased in the use of ecological understanding context to the decision making that is evidence-based, and it is provided by Shah et al. [19] presented a concept of dynamic vegetation that is stimulated by the frequent use of dynamic global vegetation models (DGVMs) over the more considerable spatial extent. The group models are frequently using the realistic model structure such as leaves and individual trees as the simulation entities, and the structures are assumed to present the vegetation, and the relevant response such as climate and the management in the provided grid cell having the typical width ranges from 10 to 250 km. Recently, the advanced development of DGVM concentrated on the considerable improvement in the physiological representation of terrestrial ecosystems as stated by Lee et al. [20].

Contrarily, Mohanty et al. [21] developed a biotic communication model like dispersal and establishment of seed, competition of plant, and mortality adopted over the larger spatial extents. Sladojevic et al. [22] presented the fixed rate of live loss of biomass representing the plant mortality rather than the mortality complexity of Spatio-temporal processes. Moreover, Too et al. [23] presented the biotic communications and vegetation's' demographic structure. These are concerned as the critical factor for the C storages' and better understanding. Recently, there has been a new class algorithms emergence, which can be loosely summarized beneath the machine learning model. Kaur et al. [24] presented the complex structures, non-linear data, and accurate predictive models generated and identified using these approaches. Mainly, Arora et al. [25] offered an emerging machine learning approach: deep learning at the top of the latest breakthrough in the vision of the computer, synthesis of speech, automatic driving and another field. Despite the generalization inherent potentially, these techniques for scaling remains underexploited in the ecological modelling to date. Therefore, the scalable vegetation dynamics (SVD) model is introduced by the author to describe the effective technique computationally with the help of DNNs for simulating transitions of vegetation [26].

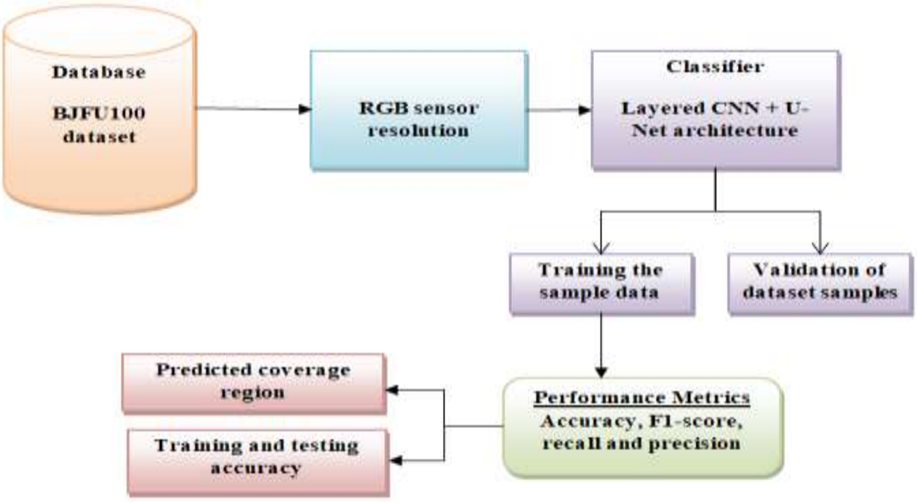

Fig 1 Generic view of the proposed model

3. Methodology

This section shows essential stages for predicting the growth of trees over the drylands. It includes dataset acquisition and classification. Here, the deep learning classifier model plays a substantial role in the prediction process. Some metrics like prediction accuracy are evaluated to show the significance of the model. Fig 1 shows the generic flow of the anticipated model.

a. Dataset description

The natural scene gives the BJFU100 dataset collected using a mobile device. In the Beijing Forestry University campus, 100 species of ornamental plants are available. Every classification has 100 photos obtained from the mobile device in natural circumstances. The prime lens of 28 mm is positioned over the smartphone equal to the RGB sensor resolution of 3120 × 4208 and focal length. Images are obtained from the low angle from the ground for tall arbours and provide the shots of low shrubs taken from a high angle. The level angle helps to take the other ornamental plants. Sizes are varied in the subjects using the magnitude order. Few images show the leaf alone, and others offer the complete plant from the provided distance.

b. Layered CNN

There is a guaranteed tool in the remote sensing technologies and the continuous process for developing in the un-preceded stage. Spatial distribution of plant communities and species provides accurate information and acts as the basis for different application fields like nature conservation management, research, agriculture, forestry, and ecosystem service assessments. The growing availability of observation data related to optical earth reveals high temporal and high spatial on the vegetation pattern, because of the theoretical sensors and frameworks like Unmanned Aerial Vehicles

(UAV) or missions with very high-resolution satellites. The optical feature space is extended further, with the structure information of vegetation canopies using the photogrammetric approaches. Effective models must fill the harness with the un-preceded source information for mapping the vegetation.
Moreover, self-learning artificial intelligence techniques are based on deep learning paved new places for the analysis of data and the vision of computers. Layered- Convolutional Neural Networks (L-CNN) is considered as the current revolutionary possibilities in the remote sensing field for detecting the object and recognizing the pattern. Contrarily, L-CNN permits more effective image, texture analysis than the general pixel-based techniques with various neighbouring pixels with contextual signals. The practical study of the textures is enabled by the L-CNNs self-learning capabilities to show the decisive leaves and vegetation species or communities are identified with the help of canopy traits. Thus this was predicted with an advanced high-resolution sensor model in tandem, and the capabilities are revolutionary by L-CNN (See Fig 2) for mapping vegetation patterns.

The autonomous L-CNN extracts the contextual features for the image dataset to learn the types of features like leaves form or flowers traits that are suitable to assign the consideration to the mentioned classifications. Since the design process of feature is not needed, the self-learning abilities of L-CNN are the significant benefit concerning the automation and computational effectiveness provided myriad ways and scale for characterizing the spatial context. The general L-CNN architecture has the important constituent to find these features that are many and consecutive pooling functions for aggregating the feature maps attained to the spatial scale from convolutions. The network's last layer has the aggregated information if the feature is specific to the target class. Therefore, the efficiency and robustness are increased in the network. Generally, these categorizations are executed with the actual resolutions of remote sensing imagery to preserve the spatial in detail. But, the L-CNN based classification has the earlier mentioned mode of the complete image is not suitable for the vegetation mapping based on remote sensing. The aim is to give the fine-grained classifications, spatially continuous in the image, such as the airborne mosaic. Therefore, the available target class is not the question; yet the location of the target class is the essential one. In addition, the robust L-CNN related technique for classifying the fine-grained image is provided using the fully convolutional networks like the remembrance and the reconstruction of the position of the contextual features. Then the extraction of contextual features is enabled by the fully convolutional networks in the broad receptive field like image extraction. The features' spatial origin is preserved, the explicit segmentation spatially, and the fine-grained segmentation of an object are generated.

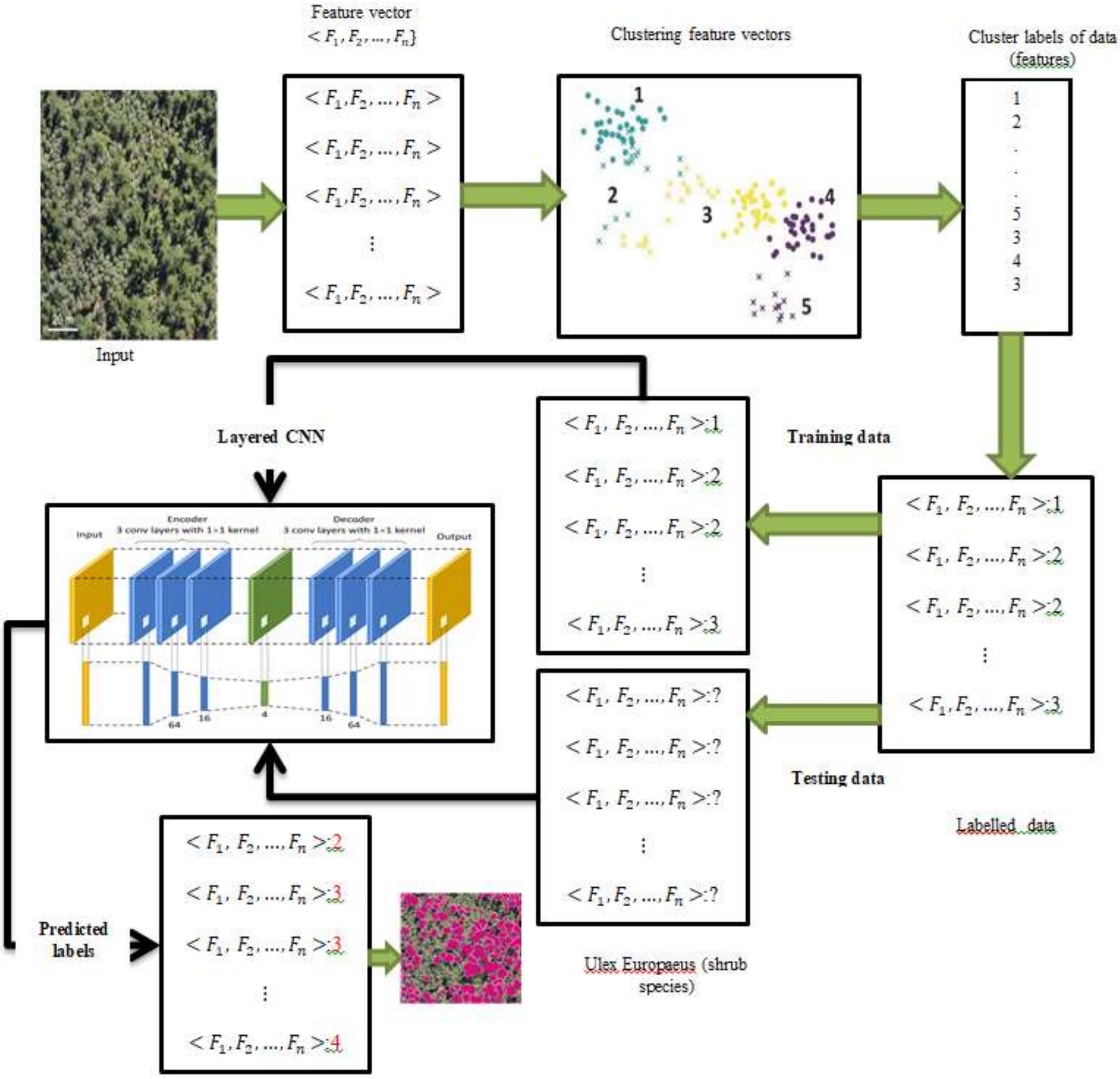

Fig 2 Layered CNN architecture model

c. Pre-trained U-Net

U-net [19] is one of the successful architectures related to convolutional networks presented in Figure 1, and it has been established in many contests. Some authors research the indication of the U-net potentially for mapping the vegetation. But, the integrated L-CNN with U-net architecture are still sparse, and the exploration of potential is not achieved completely. The L-CNN encounters bottleneck; however, training helps to explain this part. There is a need for ample references observation to learn and find the decisive image features. The reference observations are generally obtained in remote sensing vegetation that involves higher logistic efforts, inaccuracies because of the errors in geo-location, sampling, and the bias in observation. The guaranteed alternate for the practical reference in data collection is provided and to validate whether the imagery of remote sensing's spatial resolution enables visual identification and delineation of image data training is done directly. Specifically, the L-CNN segmentation technique called U-net is tested. The derivation of training data is done from the visual interpretation that permits powerful and fine-grained vegetation species mapping and the higher resolution UAV data community. The high-resolution UAV data from the RGB sensors is considered with 2D and 3D information acquired from the photogrammetry. The accuracy of segmentation for three vegetation forms is tested. They are (i) communities of herbaceous plants with the successional gradient, (ii) species of shrub-like Ulex europaeus, and (iii) trees species like Pinus radiate.

4. Numerical results and Discussion

This section discusses the outcomes of the proposed R-CNN model. The simulation is performed on Intel Core i5 processor, Windows 8 OS, and 16 GB RAM. Some evaluation criteria are considered critical for evaluating the classification performance and guiding the classifier model to improve prediction accuracy. There are five statistical measures like accuracy; sensitivity, specificity, F1-score, precision, and recall can improve classification ability. These metrics are mathematically expressed as in Eq. (1) – Eq. (5):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Specificity = \frac{TN}{FP + TN} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$F - measure = 2 * \frac{precision * recall}{precision + recall} \tag{4}$$

$$Precision = \frac{TP}{FP + TP} \tag{5}$$

a. Results

The proposed Layered CNN-with pre-trained U-Net model is elaborated in the previous section. The anticipated model attains superior accuracy than other approaches like InceptionResNet V2, MobileNet V2, InceptionV3 and EfficientNetB0. Here, various parameters are used to evaluate the performance. Based on the experimentation, three diverse representations of the images are considered, i.e. grayscale, colour, and segmented for analyzing the metrics (See Table 1 and Table 2). The metrics are discussed below:

Table 1 Parameters setup

Parameters	Value
Training epochs	30-50
Batch size	30-180
Drop out	0.2-1
Learning rate	0.01-0.0001

Table 2 Performance evaluation

Model	Accuracy (Training)	Accuracy (Testing)	Loss	Epoch	Time (s)/epochs
AlexNet	-	94.6	0.0659	50	7035
VGG	-	97.8	0.0543	50	4209
NASNet	-	92.3	-	10	-
ResNet	-	96.2	-	-	-
Deep CNN	-	93.6	-	100	-
Multi-layered CNN	97.8	96	0.2480	300	-
CNN	98	91.7	-	-	-
InceptionV3	98.2	92.4	0.0128	50	1026
InceptionResNet V2	94.7	91.8	0.0240	50	835
MobileNet V2	91.7	92.7	0.0920	50	560
EfficientNetB0	97.8	96.5	0.0090	50	560
Layered	**99.78**	**99**	**0.0091**	**100**	**545**

CNN+U-Net					

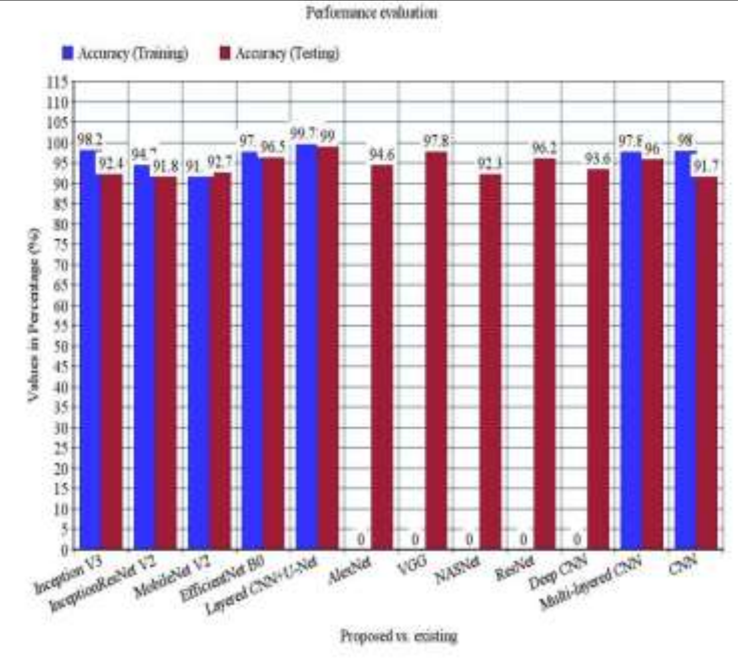

Fig 3 Training and testing accuracy

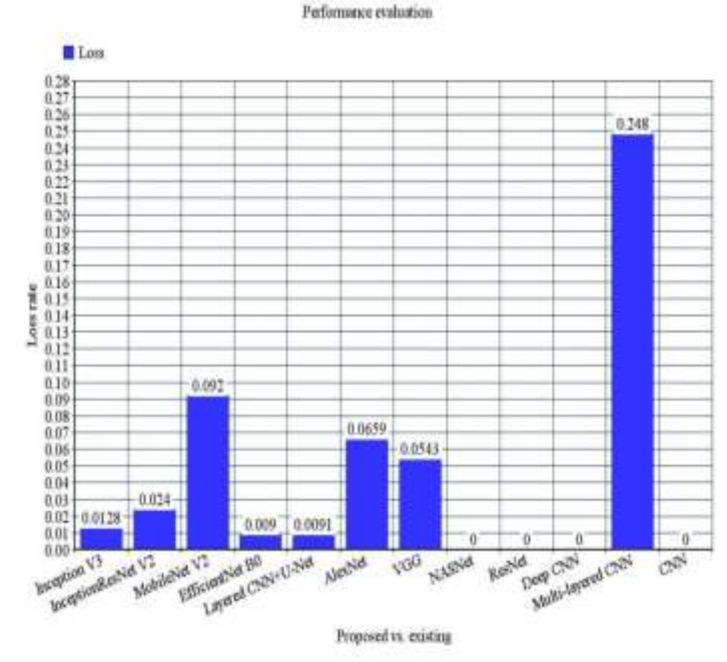

Fig 4 Loss rate comparison

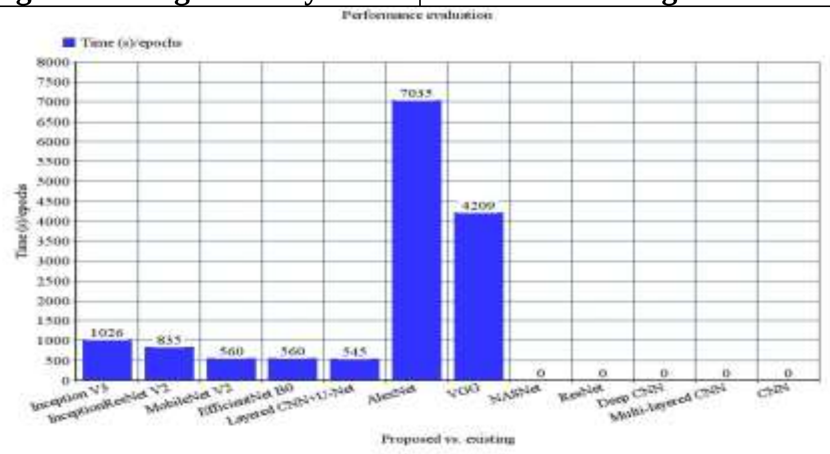

Fig 5 Time/epochs comparison

The dataset is partitioned into training and testing samples to eliminate overfitting issues. While partitioning the dataset into 80:20 (training and testing), the proposed model attains 99.78%, 98.2% for Inception V3, 94.7% for InceptionResNet V2, 91.7% for MobileNet V2 and 97.8% for EfficientNet. There is not much difference in the accuracy prediction even after partitioning the dataset into multiple ratios (See Fig 3 to Fig 5). Table 3 depicts the comparison of samples into multiple ratios.

Table 3 Performance metrics evaluation

Dataset partitioning	Model	Type	Accuracy	Loss	Epochs
Training 80% and Testing 20%	Inception V3	Coloured	92.9	0.0390	50
		Grayscale	93.9	0.1390	50
		Segment	91.7	0.0570	50
	InceptionResNet V2	Coloured	97.4	0.0730	50
		Grayscale	93.8	0.0970	50
		Segment	93.9	0.0340	50
	MobileNet V2	Coloured	97.1	0.0920	50
		Grayscale	93.5	0.1150	50

		Segment	96.9	0.0970	50
	EfficientNet B0	Coloured	95.9	0.0130	50
		Grayscale	93.8	0.0830	50
		Segment	97.9	0.0090	50
	Layered CNN+U-Net	Coloured	99.7	0.0605	50
		Grayscale	99.75	0.0610	50
		Segment	99.80	0.0615	50

Table 4 Performance metrics comparison

Approaches	Precision	Recall	F1-score
InceptionV3	96.3	91.9	93.7
InceptionResNetV2	91.2	91.6	94.9
MobileNetV2	92.9	92.6	95.8
EfficientNetB0	97.3	97.1	96.9
Layered CNN+U-Net	99.5	99.7	99.6

b. Discussion

The proposed system produces the outcomes with the line of existing research that has established the high value in deep learning for mapping the vegetation with the help of remote sensing imagery. The outcomes of the segmentation technique using L-CNN and U-Net architecture are expected to predict the species of plant and the high-resolution communities in ortho-imagery. The segmentation procedure based on L-CNN is proven accurate even though the obtained data is used with the off-the-shelf RGB sensors. The obtained outcomes exceed the accuracies of classification, which are derived on the similar test sites with the help of pixel related techniques like MaxEnt that are all together having the costly UAV-based hyperspectral imagery [6] and [25]. Here, the data is available only for Ulex europaeus and Pinus radiate. These classifications based on pixel and hyperspectral have accuracies that did not exceed 99.4% for Pinus radiate and 99.5% for Ulex europaeus. The superior technique related to L-CNN which consists of essential RGB data looks plausible to consider the relevant points. They are (i) the cognition of RGB information and also enable to differentiate the target classes visually, (ii) the L-CNN is used to find the functions resembling of the humans' visual content. This outcome shows the spectral information with high-resolution such as hyperspectral data or multispectral data that are not necessarily required to find the communities or vegetation species at the considered spatial scales.

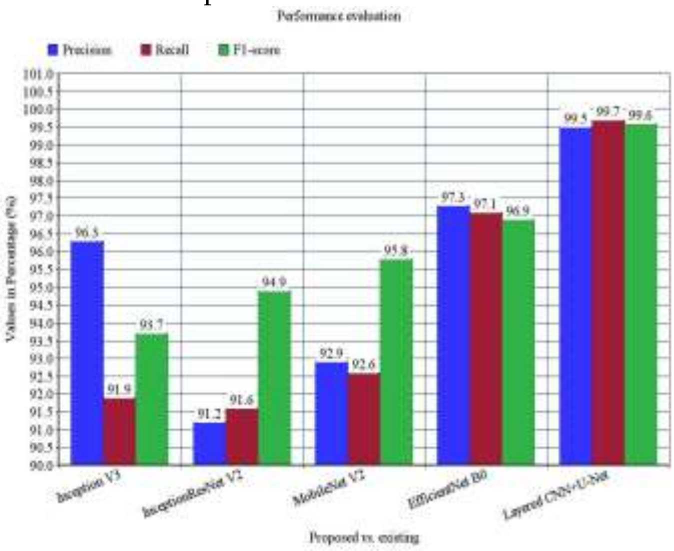

Fig 6 Precision, recall and F1-score comparison

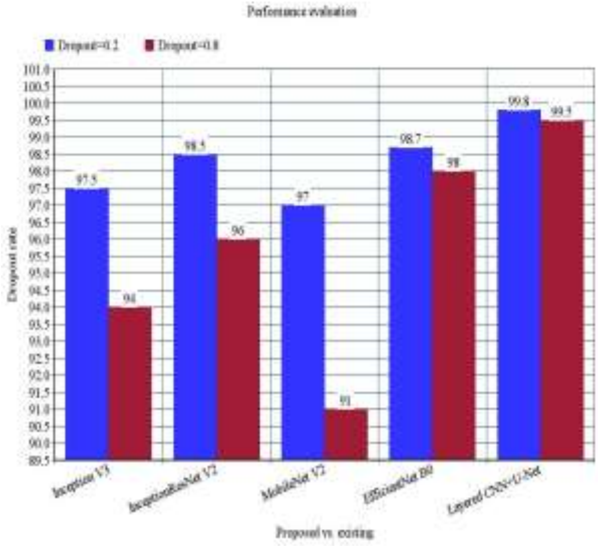

Fig 7 Dropout comparison

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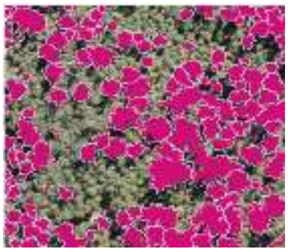
The process contrarily experiences the coarser airborne or the imagery of satellite having the pixel-based technique for classifying the communities or species of plant (See Table 4). Here, the high resolution related to spectral is generally necessary for high accuracy in classification. However, the classification techniques based on the pixel is identified unflavoured at the high spatial resolutions because of the increased class heterogeneity. Specifically, the outcomes represented with the high spatial resolutions and the spatial patterns are attained from the traits like the forms of leaf, branch pattern, and the shapes of canopy is essential for differentiating the particular communities or species of vegetation rather than the complete reference properties of plant canopy. These outcomes establish the RGB imagery in a closer range like the derivation from the mobile phones to identify the plant species. RGB synergies information has high spatial resolution and pattern recognition accurately using the deep learning techniques developed as the essential technology to operate the applications related to remote sensing. Since the remote sensing platforms are used to collect the RGB data, which were comparably less costly and easy for operating, and the data achieved is not needed for the pre-processing. The ortho-imagery spatial resolution ranges from 3 to 5 cm, like the distance of ground sampling is proved to be enough for the accurate communities and species segmentation. But, this seems plausible to increase the spatial resolution that needs to improve accuracy, like more suitable extraction of contextual features. A higher spatial resolution is essential strictly for revealing the decisive plant traits like the forms of leaves or the characteristics of branches for the few communities of species are proposed using the experiences from the closer remote sensing range.

a) Pinus radiate (tree species) before classification



b) Pinus radiate (tree species) after classification

c) Ulex europaeus (shrub species) before classification

d) Ulex europaeus (shrub species) after classification

e) Intermediate community before classification

f) Intermediate community after classification

The remote sensing imagery has the spatial resolution to evaluate whether the categorization helps reveal the target class patterns. The binary segmentation relates to presences or absences is irrelevant if the pixel size crosses the canopy components or plant organs dimensions extensively. The pixel is not associated explicitly with one class in this case. These problems can be crucial, particularly in heterogeneous and overlapping canopies. Moreover, the latest research gives the suggested outcomes for a few regions, like the categorization is restricted to represent the exact vegetation patterns. The binary segmentation applications are enhanced by enhancing the imagery spatial resolution. It suits the smooth transitions between vegetation classes identified for the plant communities as the RGB imagery and the Ulex euopaeus' sparse canopies shown in Fig 8. High-resolution data is easy to obtain and helps to increase the efficiency of segmentation techniques provided with the latest and sudden advances in the remote sensing platform and sensor technologies. Moreover, the spatial resolution is increased for the coverage of the area. This may be constrained by the complete efficiency crucially for the application of remote sensing. The continuous mapping covers values in % rather than suitable discrete classes. It shows that the L-CNN permits the prediction of cover in % of communities and species of plan in the existing research prepared in the manuscripts for the regular UAV image tiles. But, the regression technique is restricted concerning the detailed spatial mapping of the product. The cover values need to be expected for the tiles with adequate contextual features. A prerequisite approach is comprehensive reference data for plant identification based on deep learning. The L-CNN models are trained in this study with the help of reference data that are obtained using visual interpretation. The delineation is not adequate visually, yet it also benefits from traditional field-related 'ground truth' sampling. They are (i) it is unaffected using the inaccuracies of spatial, (ii) site-accessibility and the sampling bias commonly affects these sampling, (iii) this is spatially explicited to enable the user with the ortho-imagery directly than the plot data, and (iv) the higher correspondence is assigned with the features having the predictors based on the remote sensing that facilitates the statistical links in the training model. The inaccuracies are predicted, although it is visually cross-checked using an interpreter. These inaccuracies affect the training and validation process, but, it is predicted that the empirical models were found in the current study for compensating the particular error degrees of referenced data. It is necessary to consider the reference data which is application-oriented and to verify whether the communities of the target species are identified in the precise form. It is not dependent on the image quality (spatial resolution), yet the uniqueness of the morphological traits in the interest of vegetation, but, the identification of plant species based on the CNN is used only when these morphological traits are available in the plant's community.

5. Conclusion

The proposed system demonstrates the L-CNN to map accurately from the high-resolution RGB data to the vegetation communities and plant species. This mapping helps in the identification of plants at very high resolution related to spatial patterns and does not relies on spectral patterns. Here, spectral resolution is the vital for identifying the plant. The spatial and high spectral resolutions are combined for superior outcomes rather than the obtained ones. It is well-matched with the lower cost of the UAV system, which is simple to operate. The proposed technique differs from other vegetation process, that is, very accurate in the imagery of RGB. It applies to a broad range of users. The mapping of communities and plant-based species on layered L-CNN with U-Net provides the innovative places for the different applications of remote sensing related to vegetation that has the mapping of endangered species or invasive species, the mapping of habitat, or the forestry and agriculture assessments in the resource.

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