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Performance of Artificial Neural Network for Tree Species Identification Using Sentinel-2 Data

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Abstract

Accurate land cover mapping, especially concerning vegetation, is crucial for effective land use policy planning and sustainable forest management. Hence, achieving accuracy in mapping requires a deep understanding of composition changes, vegetation conditions, and the spatial distribution of tree species. In the spatial context of tree species, it holds significant potential for applications including invasive species monitoring, delineating contaminated areas, and biodiversity conservation. However, traditional methods for tree species identification are often time-consuming and costly. Exploiting remote sensing technologies presents a promising solution to this challenge, offering the ability to classify vegetation over large areas. This study focuses on utilizing Sentinel-2 satellite data and artificial neural networks (ANNs) to classify four tree species in Elpitiya DS division, Sri Lanka: tea (Camellia sinensis), rubber (Hevea brasiliensis), oil palm (Elaeis guineensis), and cinnamon (Cinnamomum verum). The ANN model achieved an overall accuracy of 78.33% in classifying these species, demonstrating the potential of Sentinel-2 images in such applications. However, accurate differentiation of rubber plantations proved challenging due to their small-scale nature and spectral similarities with other species. The research underscores the need for further model optimization to enhance accuracy and emphasizes the significance of satellite data for tree species identification. Despite promising results, continual refinement is essential to improve the model's performance. Ultimately, this study highlights the potential of ANNs as a leading classification technique for land cover mapping and tree species identification.

Keywords: Artificial neural networks (ANNs), Elpitiya DS division, Sentinel-2, tree species identification

INTRODUCTION

The global land cover is rapidly changing due to anthropogenic activities and natural processes. Agricultural expansion, urbanization, and natural disasters have made it remarkable affecting human life. Hence, effective monitoring mechanisms are required to utilize natural resources effectively for sustainable management and land use. Therefore, this study focuses on tree species classification by employing advanced classification techniques and remote sensing technologies, including artificial neural networks and multispectral imagery for better land use policy planning.

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The Importance of Tree Species Identification

Tree species level is the most basic and important component of a forest ecosystem. Hence, a detailed study of tree species is crucial for sustainable forest management. This should primarily be focused on monitoring species composition changes over time, vegetation conditions, and spatial distribution of species [1]. In this regard, the acquisition of comprehensive and up-to-date spatial data to delineate the geographical scope of the situation is essential.

Knowledge about the spatial context of tree species is not only useful in forest management but also in monitoring the spread of invasive plant species, mapping spread corridors, delineating contaminated areas [2] and crop mapping for the purposes of biodiversity conservation, nature conservation, and agriculture. However, the current distribution of tree species is influenced by several factors, including historical, ecological, and climatic conditions, natural disturbances, and anthropogenic activities. Among them, climatic change is now identified as a critical driver affecting forest ecosystems unfavorably [3].

Remote Sensing Approaches

More precise data acquisition methods are required for mapping and monitoring tree species. However, the traditional field survey protocols are costly, time-consuming, require intensive fieldwork, and often lack the necessary geospatial accuracy [4]. On the other hand, it is almost impossible to acquire comprehensive detailed tree species information over large areas purely based only on field surveys [5]. Therefore, a substitution for these traditional methods is needed to map vegetation cover and tree species precisely without having to depend on any assumptions.

In this regard, the development of satellite remote sensing techniques has revolutionized the approaches in monitoring land cover, especially for large areas [6]. Airborne cameras offer high spatial resolution, but they are limited in spectral bands. Hyperspectral images meet both spectral and spatial requirements but are costly and less available. Satellite-borne multispectral sensors provide either a few spectral bands with higher spatial resolution or more bands with lower spatial resolution [5]. Utilization of these data is also limited by weather conditions, area coverage, and acquisition time.

With the launch of Sentinel-2A/2B satellites from the European Space Agency, high-quality images with high spatial, spectral, and temporal resolution have become freely available. Sentinel-2 provides observations for the next generation of operational products such as land cover maps, land change detection maps, and geophysical variables with a high revisit frequency [7]. The 13 spectral bands of Sentinel-2 with fine spatial resolution (10, 20, 60 m), spectral resolution and several near-infrared wavelength intervals enable advanced image analysis and land cover mapping at local levels [8].

Machine Learning Algorithms

Various classification techniques are used to classify remotely sensed data based on the required accuracy and complexity of the classification process. Different algorithms, including artificial neural networks (ANNs), support vector machines (SVMs), decision trees (DTs), spectral angle classifiers, and rule-based systems are used for image classification [9]. Among them, random forests (RFs), SVM, and ANN are well known for their superior image-handling capabilities [10]. RF is widely utilized for mining and classifying hyperspectral data for plant species identification and classification [11]. On the other hand, SVM and ANN classification algorithms are predominantly explored in forest species classification using multispectral imagery [12]. ANNs are mathematical models that are similar to the structure and function of the human brain's neural network [13]. ANNs consist of interconnected nodes, called neurons, organized into layers. These layers typically include an input layer, one or more hidden layers, and an output layer [14]. Neurons in each layer receive input signals, process them using activation functions, and pass the output to neurons in the next layer. The values flow from the input layer to the output layer through hidden layers. Besides the large computational requirements of ANNs, they perform similarly or better than RF and SVM [15]. The reason for the success of ANNs can be no prior knowledge of the data distribution [16], and the ability to work with limited training samples [17].

ANNs have the remarkable ability to learn complex patterns from data through a learning process [18] called training. During training, the network adjusts the weights of connections between neurons based on the input data and desired output. Through iterative training using large datasets, ANNs can gradually optimize their parameters to accurately classify or predict outcomes. Additionally, the strength of ANNs depends on their capacity to discover complicated or detailed relationships and patterns within the dataset making them well suited for image recognition. Despite all these, the topic of tree species classification using ANN is seldom approached by the research community [1]. As there is a rarity and lack of information on how ANN classification algorithms can perform on delineating tree species using multispectral imagery, especially in the Sri Lankan context, this work will examine the utility of the Sentinel-2 satellite data for mapping tree species using ANN classification.

METHODOLOGY

Study Area

The study area includes the Elpitiya Divisional Secretariat (DS) Division of Galle district in Southern Province of Sri Lanka ranges from 6°11'59.28" N ~ 6°21'58.61" N to 80°7'54.48" E ~ 80°15'3.96" E. Elpitiya DS division covers an area of nearly 150 km^2 (Figure 1). The main land cover type of Elpitiya DS division is agricultural lands of which the main crops are tea, rubber, coconut, paddy, oil palm, and cinnamon. Accordingly, only the dominant tree species have been used for this study: tea (*Camellia sinensis*), rubber (*Hevea brasiliensis*), oil palm (*Elaeis guineensis*), and cinnamon (*Cinnamomum verum*).

Data Used in the Analysis

For this analysis, Sentinel-2 imagery from the year 2018 was used. Land use information identified from the Land Use and Land Cover (LULC) map of Sri Lanka by the Land Use Policy Planning Department (LUPPD) was collected to generate reference data. This procedure of gathering data was quite fast and reliable for the purpose of the study. Details of the data used in the study are given in Table 1.

Tree Species Data

This study used the land use database completed in early 2019 and published by the LUPPD as a reference for signature evaluation and training sample collection. The training data was collected for

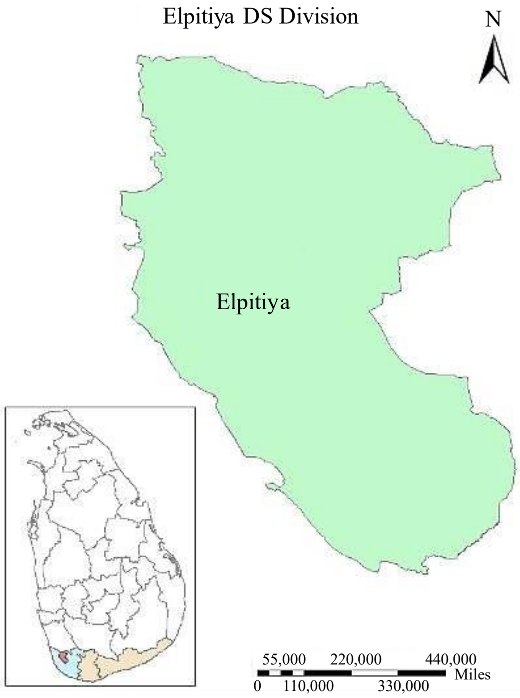

Figure 1. Location of the study area.

Table 1. Data sets and sources used in the analysis.

Data type	Sentinel-2 L2A	Land use and land cover data
Acquisition date	2018.12.17	2018
Data source	Copernicus Open Access Hub of the European Space Agency	Land use policy planning department

Table 2. Number of training and test pixels for each class.

Class name	Number of pixels	
	Training	***Test***
Tea	575	239
Rubber	347	166
Oil palm	316	130
Cinnamon	277	114

each tree species after a thorough inspection of the data layers in Google Earth Pro. The street view option was used to verify the availability of species in the sample area. Table 2 shows the number of training and test sets in each class. The number of training samples was in proportion to the abundance of the classes in the study area.

The dataset was then split into two: training and testing datasets. In all, 70% of the dataset was randomly selected as the training data and the remaining 30% was used as the test data. A sufficient number of samples were extracted for a successful classification while they were distributed consistently across the study area.

Sentinel-2 Satellite Data

The Sentinel-2 mission offers global coverage with a high temporal resolution of 5 days, high spatial resolution, and a wide field of view. The orbit is Sun-synchronous at 786 km altitude with a 10:30 A.M. descending node [19]. Sentinel-2 Level 1C (L1C) data are geometrically and radiometrically corrected images. Level 2A (L2A) data are obtained after applying atmospheric and illumination corrections on the L1C images. Accordingly, L1C images at the top of the reflectance are transformed into the L2A images at the bottom of the atmosphere reflectance.

Multiple Sentinel-2 L2A imagery corresponding to the sensing period of January 1, 2018 to December 31, 2018 was investigated. Two tiles of Sentinel-2 data were required to cover the study area. All the images were located in UTM zone 44N. Only 10 spectral bands were used for the analysis including 10 m and 20 m spatial resolution bands. The 20 m spatial resolution was resampled to 10 m using Bicubic Up sampling method in the SNAP software. The composite image was compared for classifying tree species using ANN.

METHODS

An overview of the methodology is illustrated in Figure 2. Post-processing is performed in ArcGIS 10.8 to get the final tree species map. An accuracy assessment is carried out to evaluate the analysis.

Classification

The processed Sentinel-2 L2A images composed of 10 spectral bands go through the classifier to produce a classified tree species map with four classes. Meanwhile, collected signatures are separated into training and test samples. Training data is used to train the model while test data checks the model's validity. Finally, an accuracy assessment is performed with respect to ground data points that have been verified in Google Earth to compare predictions with reality and to quantify the deviations.

Parameter Optimization

A feed forward ANN with six hidden layers was developed using TensorFlow library. ANN architectures with 2 to 512 neurons in hidden layers were tested and compared. The best performance was given by a network of 512, 256, 128, 64, 32, and 16 hidden nodes. The input layer had 10 neurons corresponding to the number of spectral bands used in the classification. The output layer had 4 neurons corresponding to the number of classified classes.

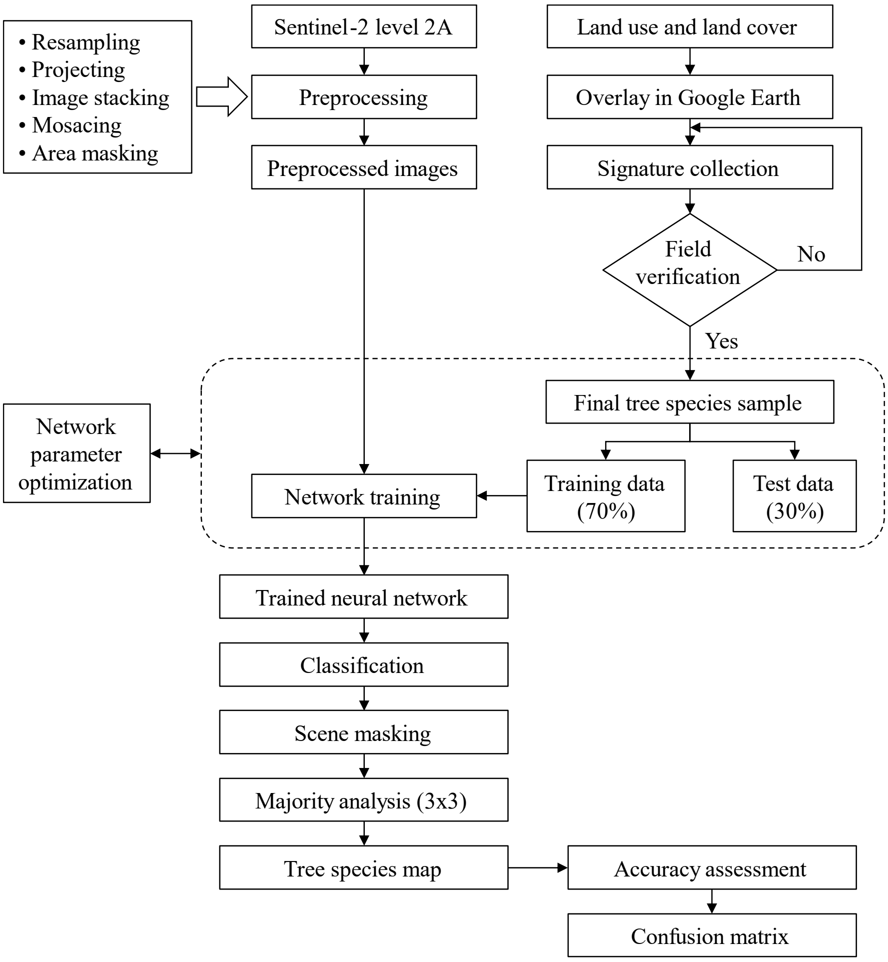

Figure 2. Overview of the research method.

A sequential model was built. Adam adaptive learning rate optimizer algorithm and sparse categorical cross entropy loss function were applied. All layers were trained using the ReLU activation function while SoftMax function was applied to the last layer. The epoch hyperparameter was set to 500. The model tended to overfit beyond this value. Learning rate was set to 0.0001. It is important to note that the parameters in the classification were based on the user experience and experimental testing. The training and classification were performed in Jupyter Notebook.

Accuracy Assessment

Stratified random sampling was used to generate the data points where the number of points is proportional to the relative area of the class it belongs. The validation of the ground points is checked in Google Earth Pro street view. If it fails to be identified, the points are assigned to the nearest possible clear site for future analysis.

For the analysis, 60 sample points were generated. The accuracy of the experiment is then assessed by a confusion matrix for comparison. Accordingly, overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and kappa coefficient can be calculated. The confusion matrix provides information of the estimation against the reality and presents the error on the map [20].

RESULTS AND DISCUSSION

Artificial Neural Network Model

The same model was tested for different parameters to obtain the best results. In every instance, the seed for the random number generator in TensorFlow was set to a specific value. This ensured the sequence of random numbers generated was reproducible across different code runs. This was particularly useful for debugging and ensuring consistent behavior during experiments. Accordingly, the model achieved the training classification accuracy of 73.2%.

Classification of Tree Species

Figure 3 shows the final vegetation map of the four tree species classified using ANN. The resultant spatial distribution is relatively heterogeneous when compared with the land use and land cover map issued by the LUPPD. Built up area, bare land, forest land, and water features were masked out from the classified raster based on the LULC data. Accordingly, tea obtained the largest area of 5336.368 ha while rubber achieved the smallest area, 867.5466 ha (Table 3) in the final map. Table 3 also shows area percentages based on the study area.

Accuracy Evaluation

ANN achieved an overall classification accuracy (OA) of 78.33% followed by a kappa coefficient at 0.69. The user's accuracy (UA) for tree species classes ranges between 70% and 84% where UA for

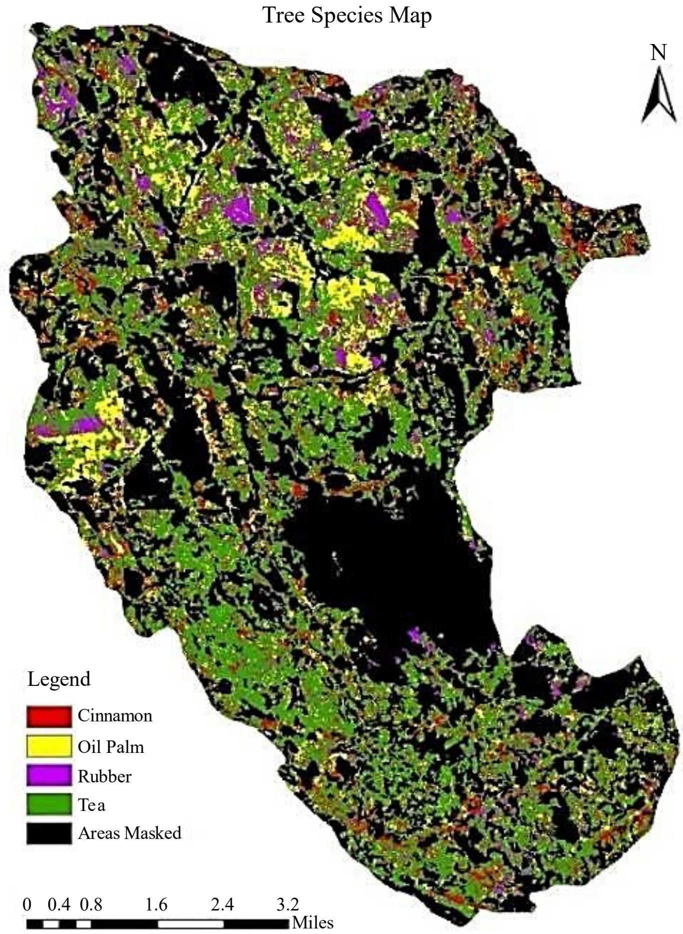

Figure 3. Vegetation map of the tree species.

Table 3. Extent of each class.

Class	Extent (ha)	%
Tea	5336.368	35.57579
Rubber	867.5466	5.783644
Oil palm	1058.904	7.05936
Cinnamon	1285.836	8.57224

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Table 4. Confusion matrix of the final map.

	C1	C2	C3	C4	Total	UA
C1	7	0	1	2	10	0.7
C2	1	8	0	1	10	0.8
C3	0	2	10	0	12	0.83
C4	3	0	3	22	28	0.79
Total	11	10	14	25	60	0
PA	0.64	0.8	0.71	0.88	0	0.78
OA	78.33%					
Kappa	0.690722					

rubber is the highest and all other classes are below 80%. The producer's accuracy (PA) ranges between 63% and 88%. Overall, all the classes are classified with higher UA and PA where all accuracies are more than 50% (Table 4).

DISCUSSION

This study focuses on the evaluation of an ANN model to classify the most common tree species in Elpitiya DS division. The work will also search for the possibility of using Sentinel-2 satellite images, especially in the Sri Lankan context.

Classification of Tree Species

Identifying tree species is quite a challenging task in a country like Sri Lanka with huge variations in vegetation. However, this study has shown that Sentinel-2 data is suitable for tree species classification but with a suitable classification technique. It is important to compare the results of the analysis and LUPPD for better clarification. The created tree species map was used to calculate the species composition after the classification.

The area increment during the analysis may be due to the classification of other agricultural lands ex: paddy, coconut, and mixed trees into the four classes. Accordingly, all the species have increased in extent except for rubber as indicated by Figure 4 between LUPPD and classified data. Hence, the analysis has failed to fulfill the minimum requirement related to class rubber.

In 2018, 70% (89,243 ha) of rubber cultivation was owned by small-scale rubber cultivators and 30% (37,442 ha) by the state estate sector (owned by 20 local plantation companies and government agencies). Accordingly, a large part of rubber cultivation is done by small-scale growers [21]. This information along with LUPPD land use data, overlay in Google Earth Pro suggests that Elpitiya DS division has a majority of small-scale rubber cultivations. These small-scale lands may have been misclassified due to spectral overlaps between other tree species which led to mixed pixels. On the other

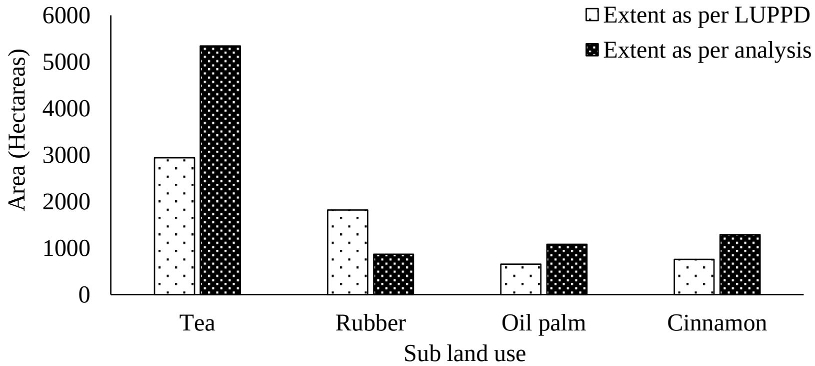

Figure 4. Area comparison between land use policy planning department (LUPPD) and classified data.

hand, the spatial resolution of Sentinel-2 images (10 m) may have affected the classification to a greater extent. This explains the area reduction of rubber extent during the analysis. More ground truth samples could be required to improve the accuracy in such a case.

The selection of training samples is also a challenging task in this type of analysis. The samples should be statistically spectral different for generating a good accuracy of the classification [8]. But there may be cases where plantations include small patches of another species lesser or slightly greater than the extent covered by a pixel making it further difficult to decide samples. Therefore, it is a must to acquire expert knowledge before any analysis.

Few places were identified as clearings on Sentinel-2 images that contradicted the LULC data. This suggested that these areas were cleared between LULC data collection and satellite data acquisition. It may be due to LULC data from LUPPD have been completed in 2018 but data collection started from 2016 [22].

Potential of Sentinel-2 Images

The overall accuracy of the analysis was 78.33%. This result indicates that multi-temporal Sentinel-2 images have great potential for tree species classification. Clark (2020) states that Sentinel-2 images outperform Landsat data in mapping detailed floristic association [23]. The latter is not sufficient to classify heterogeneous tree compositions accurately. However, higher spatial resolution data at a local level are capable of fine discrimination of tree species [24]. Despite their potential, it is important to acknowledge the limitations of these data, including their availability, cost, processing requirements, and high dimensionality. In this regard, Sentinel-2 imagery is a better solution to deal with. On the other hand, previous studies had proven that Sentinel-2 data with a resolution of 10 m, 20 m, and 60 m can still provide better accuracies with the adequate spectral information and unique band setting for the purpose of tree species delineation [15]. Furthermore, the higher temporal resolution of sentinel mission allows users to deal with plenty of information. Accordingly, this study highlights the utility of satellite data and demonstrates the potential of Sentinel-2 imagery in identifying tree species using ANN classification.

Performance of Artificial Neural Network

This analysis resulted in a training accuracy of 73.2%. Though the accuracy is higher, it is suggested that the model requires further hyperparameter tuning. A robust method would be a better approach in this regard than solely depending on the user experience and experimental testing. Hence, a tedious process will be required in developing, compiling, and training the model. The addition of new layers would increase the accuracy but increase the complexity of the model. Therefore, analysis might not be possible on every computer.

Although ANNs have the ability to work with limited training samples, few training samples may fail the outcome of a model while large dataset may cause overfitting. The quality of the sample data is also a crucial factor which determines the accuracy of the ANN classification. On the other hand, the slightest change in the model can result in overfitting or underfitting causing law classification accuracies.

It is also important to note that ANN was unable to deal with the spectral variations of some species during the analysis, for example, rubber [25]. Lu and Weng (2007) state that this is one of the most 26 common problems during per-pixel classification technique [25]. Accordingly, it explains why the ANN classifier did not obtain the optimum accuracy. However, confusion matrix showed that most of the pixels are correctly classified. Thus, the findings demonstrate the successful application of ANNs to the identification of tree species in Elpitiya DS division.

CONCLUSION

The use of advanced remote sensing techniques, specifically multispectral images, and machine learning algorithms have been utilized for the identification and classification of tree species based on the most common crops tea, rubber, oil palm, and cinnamon found in Elpitiya DS Division, Sri Lanka in this research. Accordingly, it can be stated as a success in the analysis of multispectral imagery using ANN classification method.

The developed ANN model achieved a higher overall accuracy of 78.33% with a few false positives highlighting the potential of multispectral unmanned aerial vehicle (UAV) technology for local-scale vegetation monitoring and species detection. Moreover, the analysis revealed that the sensitivity of the parameters in the model enhances the accuracy of tree species classification. Additionally, we determined that ANN is preferable in areas with limited but qualitative training samples. However, experimenting with recurrent neural network (RNN) and convolutional neural network (CNN) would be a better approach than ANNs as such deep learning architectures may enhance model robustness and generalization capabilities.

Summary

In summary, research findings provide a better idea about the applicability of remote sensing methodologies for vegetation analysis and management. It shows that smart technologies, including multispectral imaging coupled with machine learning algorithms, can effectively improve accuracies. However, ANN is still tedious, extremely time-consuming, and Omer et al. (2015) state that challenges related to ANNs include the likelihood of involving local extremum, a lack of strict design packages with a theoretical foundation, the difficulty to control the training process, and encountering overfitting problems on the test dataset. Therefore, it is the researchers' or users' choice to select the most appropriate and efficient approach for their needs based on the purpose of the work, accuracy required etc.

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REFERENCES

1. Raczko E, Zagajewski B. Tree species classification of the UNESCO Man and the Biosphere Karkonoski National Park (Poland) using artificial neural networks and APEX hyperspectral images. Remote Sensing. 2018; 10 (7): 1111.
2. Follak S, Schleicher C, Schwarz M. Roads support the spread of invasive in Austria. Die Bodenkultur: J Land Manage Food Environ. 2018; 69 (4): 257–265.
3. Móricz N, Rasztovits E, Gálos B, Berki I, Eredics A, Loibl W. Modelling the potential distribution of three climate zonal tree species for present and future climate in Hungary. Acta Silvatica et Lignaria Hungarica. 2013; 9 (1): 85–96.
4. Omer G, Mutanga O, Abdel-Rahman EM, Adam E. Performance of support vector machines and artificial neural network for mapping endangered tree species using WorldView-2 data in Dukuduku forest, South Africa. IEEE J Select Top Appl Earth Observ Remote Sensing. 2015; 8 (10): 4825–4840.
5. Immitzer M, Atzberger C, Koukal T. Tree species classification with random forest using very high spatial resolution 8-band WorldView-2 satellite data. Remote Sensing. 2012; 4 (9): 2661–2693.
6. Phiri D, Simwanda M, Salekin S, Vyirenda VR, Murayama Y, Ranagalage M. Sentinel-2 data for land cover/use mapping: a review. Remote Sensing. 2020; 12 (14): 2291.
7. Drusch M, Del Bello U, Carlier S, et al., Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sensing Environ. 2012; 120: 25–36.
8. Rujoiu-Mare M-R, Olariu B, Mihai B-A, Nistor C, Săvulescu I. Land cover classification in Romanian Carpathians and Subcarpathians using multi-date Sentinel-2 remote sensing imagery. Eur J Remote Sensing. 2017; 50 (1): 496–508.
9. Hamad R. An assessment of artificial neural networks, support vector machines and decision trees for land cover classification using Sentinel-2A data. Sciences. 2020; 8 (6): 459–464.

10. Adelabu S, Mutanga O, Adam E, Cho MA. Exploiting machine learning algorithms for tree species classification in a semiarid woodland using RapidEye image. J Appl Remote Sensing. 2013; 7 (1): 073480.
11. Verikas A, Gelzinis A, Bacauskiene M. Mining data with random forests: a survey and results of new tests. Pattern Recogn. 2011; 44 (2): 330–349.
12. Nitze I, Schulthess U, Asche H. Comparison of machine learning algorithms random forest, artificial neural network and support vector machine to maximum likelihood for supervised crop type classification. In: Proceedings of the 4th GEOBIA, Rio de Janeiro, Brazil, May 7–9, 2012. pp. 035–040.
13. Brilliant.org. Artificial Neural Network. [Online]. March 18, 2024. Available at https://brilliant.org/wiki/artificial-neural-network/
14. 14Civco DL. Artificial neural networks for land-cover classification and mapping. Int J Geogr Inform Sci. 1993; 7 (2): 173–186.
15. Xi Y, Ren C, Tian Q, Ren Y, Dong X, Zhang Z. Exploitation of time series Sentinel-2 data and different machine learning algorithms for detailed tree species classification. IEEE J Select Top Appl Earth Observ Remote Sensing. 2021; 14: 7589–7603.
16. Hasan M, Ullah S, Khan MJ, Khurshid K. Comparative analysis of SVM, ANN and CNN for classifying vegetation species using hyperspectral thermal infrared data. Int Arch Photogramm Remote Sensing Spatial Inform Sci. 2019; 42: 1861–1868.
17. Dixon B, Candade N. Multispectral landuse classification using neural networks and support vector machines: One or the other, or both? Int J Remote Sens. 2008;29(4):1185-206. doi: 10.1080/01431160701294661.
18. Mas JF, Flores JJ. The application of artificial neural networks to the analysis of remotely sensed data. Int J Remote Sensing. 2008; 29 (3): 617–663.
19. Gascon F, Bouzinac C, Thépaut O, et al. Copernicus Sentinel-2A calibration and products validation status. Remote Sensing. 2017; 9 (6): 584.
20. Adiningrat DP. Mapping Dominant Tree Species from Remotely Sensed Image Using Machine Learning Algorithms. MSc Thesis. Enschede, Netherlands: University of Twente; 2017.
21. Agricultural Statistics at a Glance 2018. Directorate of Economics and Statistics, Department of Agriculture, Cooperation & Farmers Welfare, Ministry of Agriculture & Farmers Welfare, Government of India. 2019.
22. LUPPD: Land Use Policy Planning Department, editor. Land Use and Land Cover of Sri Lanka. Colombo, Sri Lanka: Land Use Policy Planning Department; 2019.
23. Clark ML. Comparison of multi-seasonal Landsat 8, Sentinel-2 and hyperspectral images for mapping forest alliances in Northern California. ISPRS J Photogramm Remote Sens. 2020;159:26-40. doi: 10.1016/j.isprsjprs.2019.11.007.
24. Soleimannejad L, Ullah S, Abedi R, Dees M, Koch B. Evaluating the potential of Sentinel-2, Landsat-8, and IRS satellite images in tree species classification of Hyrcanian forest of Iran using random forest. J Sustain Forestry. 2019; 38 (7): 615–628.
25. Lu D, Weng Q. A survey of image classification methods and techniques for improving classification performance. Int J Remote Sensing. 2007; 28 (5): 823–870.

