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Assessment of Random Forest and Neural Network for Improving Land Use/ Land Cover Mapping from LIDAR Data and RGB Image: A Case Study of Magaga-El-Menia Governorate, Egypt

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Abstract

The goals of this article are to improve classification of land use/land cover information using LIDAR data and RGB images, as well as to compare the performance of various supervised machine learning classifiers (random forest and neural network) for extracting land use/land cover information. The 3D coordinates are first transferred to a high-resolution raster via interpolation. Height and intensity raster grids are formed. Second, various raster maps - a normalized digital surface model (nDSM), the difference of returns, and the LiDAR intensity image -are combined to create a multi-channel image. Five scenarios with different combinations were created. Finally, on the five separate datasets, several classifications based on random forest and neural network classifiers were performed. The classification findings were subjected to a quantitative accuracy check. A comparison of these five methodologies has been conducted. Following that, morphological operations were used to eliminate noise. The results revealed also that the fourth approach is the best followed by the third approach then the last approach then the second approach followed by the first approach. It was discovered that random forest classification outperforms neural network classification in terms of classification accuracy.

1. Introduction

Given the expanded availability of RS image archives, land use, and land cover (LULC) mapping is the most prevalent application of RS data for a variety of environmental investigations (Sheykhmousa et al., 2021). The LIDAR method is very promising and can be used to detect 3D objects. A laser scanner, a GNSS receiver, and an Inertial Navigation System (INS) are the most common components of an airborne LIDAR system (Diab et al., 2022; Zeng, 2008; Uzar, 2013). LiDAR is a dependable approach for gathering elevation data at many surface levels based on the laser beam's penetration through the ground. The recorded intensity of the backscattered laser beam can be used to classify surface items, and the elevation data can be utilized to produce a digital elevation Model (DEM). The first returns in vegetated areas often correspond to the upper landscape canopy level (e.g., vegetation tops), whereas the last returns correspond to the terrain surface. The first returns are utilized to create Digital Surface Model (DSM), while the last returns are used to create Digital Elevation Model (DEM) (Azizi et al., 2014). Intensity data, on the other hand, have the disadvantage of being undersampled and consequently exceedingly noisy (Rottensteiner et al., 2005). Because of their spectral composition and higher resolution than laser scanner data, multispectral images can provide useful information (Rottensteiner et al., 2005).

Image classification for land use and land cover mapping is also an important component in many remote sensing applications. However, due to data limitations, image processing techniques, and the complexity of the land use/land cover types, it is difficult to generate a satisfactory result for land use/land cover classification from remotely sensed data. Many factors must be considered in order to achieve good classification accuracy, including the study area's characteristics, the availability of suitable remotely sensed data and ground reference data, the proper use of variables and classification algorithms, the producer's experience, and the time constraint (Wong & Sarker, 2014).

The process of converting Digital Number (DN) values to significant land cover information at each pixel location in an image is known as image classification (Akar & Güngör, 2012). There are various algorithms in machine learning (ML) that can be used for classification and having their pros and cons (Sharma et al., 2020). Supervised machine learning has shown great promise in the field of Land Use/ Land Cover Mapping. This approach involves training a machine learning model on labeled data, allowing it to learn to recognize different features. The model can then be used to classify features in new data, providing quick and accurate analysis (Rashdi et al., 2023). Land-cover maps can be obtained efficiently by converting 3D airborne multi-spectral LiDAR point cloud into 2D feature images and applying well-known machine learning algorithms (e.g., support vector machine, decision tree, and random forest) (Pan et al., 2020).

Even though a lot of research has been done on LiDAR classification in terms of features, data format, and classifier selection or design (Wang et al., 2019), there are still certain issues with the current algorithms and selected features, necessitating more work. This paper aims to fill this gap by investigating the benefits of utilizing fusion of LiDAR and RGB image as a powerful data source for improving land cover mapping using five different features of LiDAR and RGB and exploring the effectiveness of two machine learning algorithms Random-forest (RF) and Artificial Neural Networks (ANNs) for land cover mapping. A number of studies have investigated the potential of Random-forest (RF) classification to improve urban object classification from airborne LiDAR data (Chehata et al., 2009); Niemeyer et al. (2014), as well as for mapping reforested landslides using variables calculated either for each pixel (Chen et al., 2014) or for image objects delineated by segmentation (Li et al., 2015; Belgiu & Dra˘gut,2016).

Artificial Neural Networks (ANNs), on the other hand, could be a useful alternative for mapping land cover for such high-dimensional images. The statistical distribution of the input pattern classes is not assumed by ANNs (Hugo et al., 2007). An artificial neural network (ANN) is a type of artificial intelligence that mimics some of the operations of the human brain. Weighted connections connect all neurons on a given layer to all neurons on the preceding and subsequent layers (Foody & G.M., 1999). An ANN is made up of layers, each of which has a collection of processing units (neurons). ANNs have two key characteristics: the ability to learn from input data and the ability to generalize and predict previously unseen patterns depending on the data source rather than any specific a priori model. ANNs learn about the regularities in the training data during the training phase and then develop rules based on these regularities that may be applied to unknown data (Foody & G.M., 1999).

A number of studies have investigated the potential of neural network classification to improve land cover classification from LiDAR data with other data (Minh & Hien, 2011; Nguyen et al., 2005; Priestnall et al., 2000), Many recent studies have combined LiDAR with multispectral imagery. One example of integration can be found in Hartfield et al. (2011). The authors investigated the feasibility of combining remotely sensed multispectral reflectance data and LiDAR-derived height information to improve land use and land cover classification and analyzed the data using classification and regression trees. In this study, Antonarakis et al. (2008) used elevation and intensity airborne LiDAR data to classify forest and ground types quickly and efficiently without the need for manipulating multispectral image files, employing a supervised object-oriented approach.

Traditionally, LiDAR has been used to classify LiDAR into features such as buildings (Axelsson, 1999) and vegetation (Mason et al., 2003; Cobby et al., 2003). Until recently, there had been little progress in using LiDAR point cloud data with elevations and intensities for land cover classifications. Brennan & Webster

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(2006) attempted classifications by using derived LiDAR surfaces to differentiate between different layers. They used four layers in their research (mean intensity, normalized height, digital surface model, and multiple Waveform LiDAR returns). LiDAR has traditionally been used to classify LiDAR into features such as buildings (Axelsson, 1999) and vegetation (Mason et al., 2003; Cobby et al., 2003). Until very recently, not much had been achieved by using LiDAR point cloud data with elevations and intensity for land cover classifications. Classifications have been attempted by Brennan & Webster (2006) who used derived LiDAR surfaces to differentiate between different layers. Their study used four layers (mean intensity, normalized height, digital surface model, and multiple waveform LiDAR returns).

Schenk & Csatho (2002) proposed using the complementary properties of LIDAR data and aerial imagery to first achieve a more complete surface description through a feature-based fusion process, and then extract semantically meaningful information from the aggregated data. They stated that LIDAR data are particularly useful for detecting surface patches with specific geometrical properties and deriving other properties such as roughness. Aerial images, on the other hand, can aid in determining surface boundaries and the locations of surface discontinuities. Haala & Brenner (1999), combined a normalized DSM from LIDAR data with three spectral bands from a scanned color infrared (CIR) image. Because the separation of trees from buildings is the most difficult task in this context due to the relatively low resolution of the LIDAR data, the near-infrared band must be included in the classification process. Instead of using all bands of multispectral images, the normalized difference vegetation index (NDVI) derived from the near-infrared and red portions of the spectrum can be used for its potential in vegetation discrimination (Lu & Trinder, 2003).

Besides LiDAR height and intensity, NDVI, LiDAR point features, there are a few studies exploiting the characteristics of multiple returns of LiDAR data to facilitate land cover classification. By investigating the first and the last LiDAR data returns, individual (height or intensity) features or the difference among these features can be derived to increase the feature spaces (Yan et al., 2017). Wijaya et al. (2023), tested the ability of airborne LiDAR data to classify mangrove vegetation structures conducted in Ratai Bay, Pesawaran District, Lampung Province. The classification system applied integrates structure attributes of lifeforms, canopy height, and canopy cover percentage. Airborne LiDAR data are derived into canopy height models (CHM) and canopy cover percentage models, then grouped by examining statistics and the zonation distribution of mangroves in the study area. The results of this study show that airborne LiDAR data are able to map vegetation structures accurately.

Given the wide range of input datasets that might be used to improve categorization, it's critical to include only the most relevant datasets to reduce computational burden without sacrificing accuracy (Corcoran et al., 2013). In this case, an RF classifier was utilized to assess each data source's contribution to the classification results (Gislason et al., 2006; Corcoran et al., 2013). The novelty of this study is that we investigated improving the classification accuracy of machine learning algorithms by using the integration of LIDAR-derived layers and RGB images. Two different classifiers, random forest and artificial neural network (ANN), were used in this study to classify the five different datasets. The objectives of this study were to (1) Investigate the potential of random forest and neural networks for automatic feature detection from LIDAR data and RGB image; (2) Improving Land use/ land cover mapping from LIDAR data and RGB images. In this context, RF and neural network classifiers have been used to evaluate the contribution of each data source to the classification results.

2. Data and Methods

2.1. Study Area and Data Sources

The airborne LiDAR data and digital aerial photographs used in this study were obtained from flights organized by the national authority of Remote Sensing and space sciences on 2017. The airborne LiDAR had an average flying height of 1500 m collecting first and last pulse data with an average point density of 0.6/ m, and an average spatial resolution of 0.1 µper m. The study area was chosen at Magaga-El-Menia Governorate,

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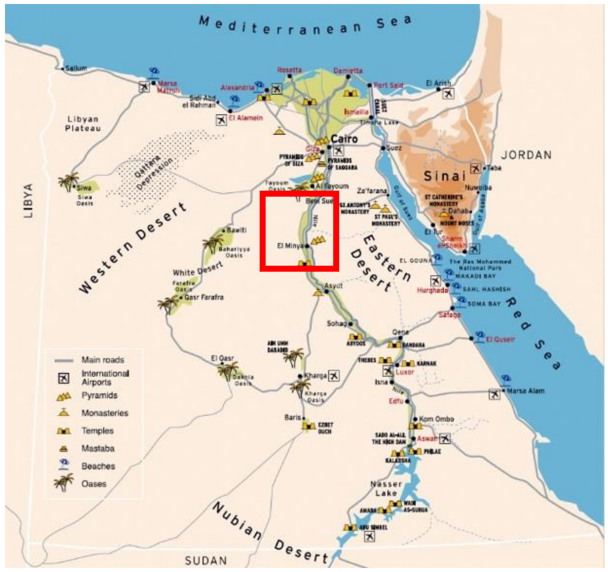
Egypt (Figure 1). The study area, comprising 1.92 km^2. The following data Sources are used is (1) LIDAR point cloud captured with Trimble AX60 scanner contains the first and the last echoes of the laser beam. According to the specification of the laser scanner, it delivers very high point densities, 83,000 measurements per second; the average measurement density is 0.1 measurements/m^2; the vertical accuracy of LIDAR data is 10 cm; and the horizontal accuracy is 4 cm; and (2) RGB image with a resolution of 6 cm.



Source: Mapsland

Figure 1. Study Area

2.2. Methodology

In this section, the processing chain that has been carried out for improving land cover mapping from LIDAR Data and RGB Image data set was discussed. Figure 2. illustrates the methodological flowchart of the present investigation. The processing steps as follows:

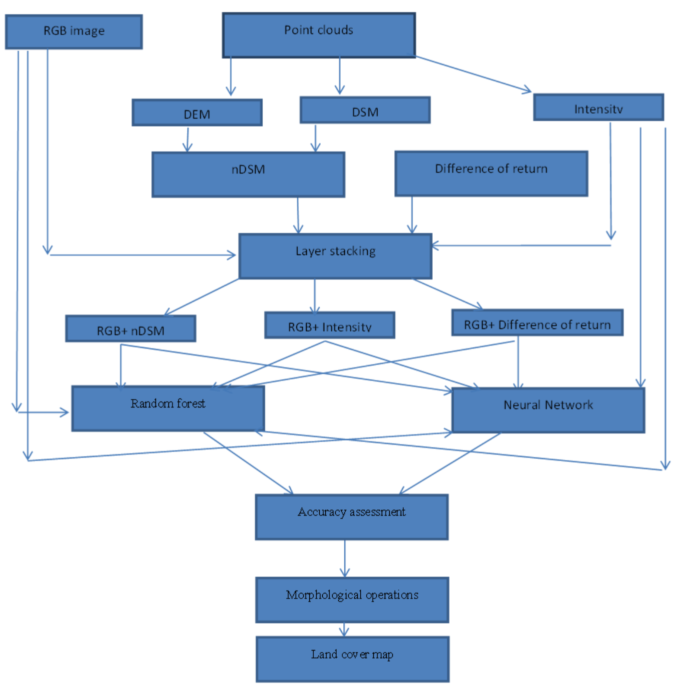


Figure 2. The Methodological Flowchart of the Present Investigation

Initially, LIDAR DSM and DTM were generated; nDSM was calculated; Cloud compare was used for derivation of LIDAR metrics (intensity, return difference); Noise filtering of intensity images was performed; Subsetting of intensity, nDSM, return difference, and RGB images; Coregistration of different feature sets. After that, Random Forest classification and neural networks have been used for feature detection. Classification was performed using five different approaches. In the first approach, classification is done using intensity image while in the second approach, classification is done using three RGB channels while in the third approach, classification is done using three RGB channels and intensity image. In the fourth approach, classification is performed using three RGB channels and a normalized digital surface model (nDSM). In the last approach, the classification was performed using a combination of three RGB channels and difference results; the classification accuracy was assessed using overall accuracy and kappa coefficient. Seventy randomly selected points were used for this purpose; morphological operations were performed to remove noise.

2.3. Point Cloud Filtering

During the pre-processing stage, the point cloud data were filtered to remove noise and superfluous data, and smoothing operations were done**.** In the processing phase, the point cloud data were processed**.**

2.4. LIDAR-derived metrics

LiDAR derivative layers were generated using cloud compare.

2.4.1. Digital Surface Model (DSM)

Airborne Light Detection And Ranging (LiDAR) technology allows for the quick gathering of high-resolution surface elevation data, which is useful for a variety of applications (Priestnall et al., 2000; Bartels & Wei, 2006). The LiDAR data was used to create a DSM that contained both vegetation and buildings. The first echo has been used to generate a DSM using cloud compare, this DSM raster was interpolated from ALS point cloud data with a grid width of 20 cm**.** Figure 3. illustrates LIDAR DSM.

2.4.2. Digital Elevation Model (DEM)

The LiDAR data was used to create a DEM that contained the bare earth last returns are used for the generation of digital terrain models (DTM). Figure 3. depicts LIDAR DSM and Figure 4. illustrates LIDAR DEM.

2.4.3. Intensity Image

The ratio of the strength of the light reflected off an object to the light emitted can be defined as LiDAR intensity (Song et al., 2002). Gray-scale-coded objects are better differentiated using the intensity image (Uzar, 2013). Figure 5. depicts intensity. Figure 6. depicts a swipe of RGB image and intensity.

2.4.4. Normalized Digital Surface Model (nDSM)

The nDSM is produced using raster map algebra to subtract the DTM from the DSM (Zhu et al.,2011). This feature will help distinguish elevated objects from ground or non-ground objects (Guan et al,2012). Figure 7. depicts nDSM.

2.4.5. Difference of Returns

The height difference between echoes (FL-Diff= First echo - last echo): This feature will help distinguish high-rise penetrable vegetation (Guan et al, 2012). Figure 8. Illustrates the difference of return.

2.5. Feature Detection using Classification

There are four types of land covers identified such as urban, vegetation, road, and water. The land cover classification was implemented with the existing data sets using five approaches. To evaluate the appropriate

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classification method for the LiDAR data, two classification methods were used such as random forest and neural network classifier.

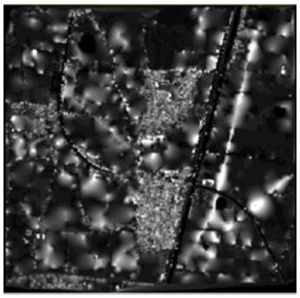

Figure 3. LIDAR DSM

Figure 4. LIDAR DEM

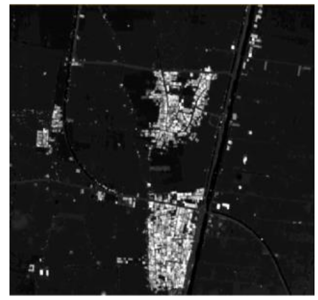

Figure 5. Intensity

Figure 6. The Swipe of RGB Image and Intensity

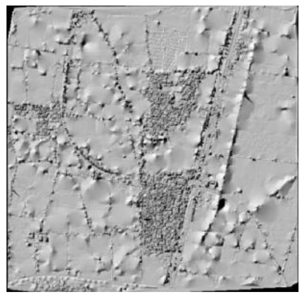

Figure 7. nDSM

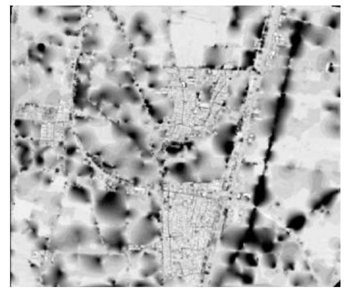

Figure 8. Difference of Return

3. Results and Discussion

Land use/ land cover mapping is important in urban planning, environmental study and resource management. The goal of this study is to evaluate if LiDAR and RGB data can be used to improve land cover categorization, as well as investigate which machine learning classification algorithm is best for the LIDAR data and RGB image. Random Forests (RF) and Neural Networks (NN) classifiers are experimentally compared to examine their performances in the field of land cover classification of airborne LIDAR data and RGB image. Despite the fact that LiDAR classification has been extensively researched in terms of features, data format, and classifier selection or design. Several problems remain with the present methods and features that have been chosen.

3.1. Land Cover Classification

3.1.1. Random Forest

The random forests algorithm is a machine learning technique that is increasingly being used for image classification. Random forests is an ensemble model which means that it uses the results from many different models to calculate a response. In most cases, the result from an ensemble model will be better than the result from any one of the individual models. In the case of random forests, several decision trees are created (grown) and the response is calculated based on the outcome of all of the decision trees (Horning,2010; Dahinden 2009). The main advantages of the Random Forest Algorithm are (Tokar et al,2018):

1. Its accuracy is as good as Adaboost's and sometimes better.
2. It's relatively robust to outliers and noise.
3. It's faster than bagging or boosting.
4. It gives useful internal estimates of error, strength, correlation, and variable importance.
5. It's simple and easily parallelized.

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The trees number was set to 1000.

Figure 9 illustrates classification using the random forest classifier (the best scheme number four). Figure 10 illustrates the overall classification accuracy and Kappa coefficient for the five approaches of the two classifiers.

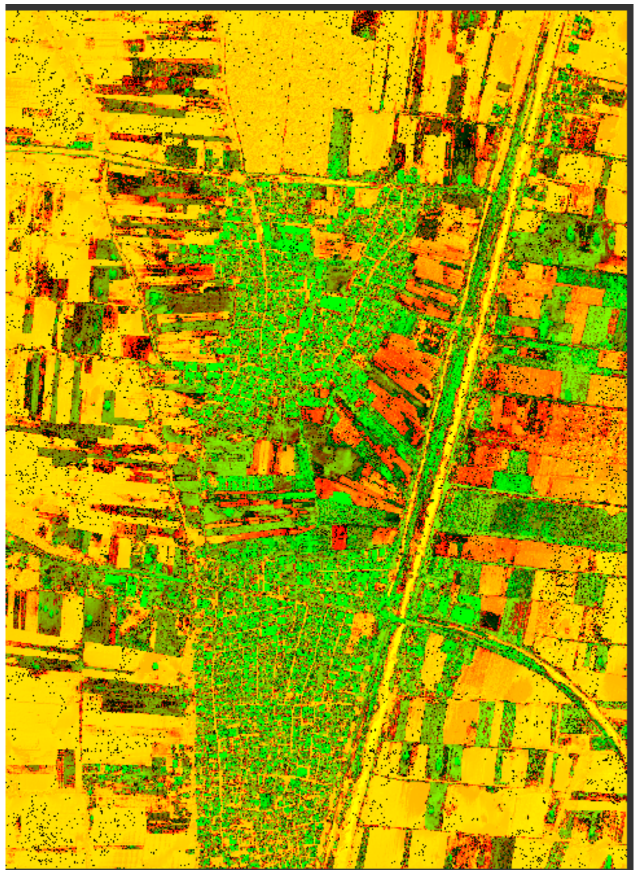

Figure 9. Classification using the Random Forest Classifier (the best scheme).

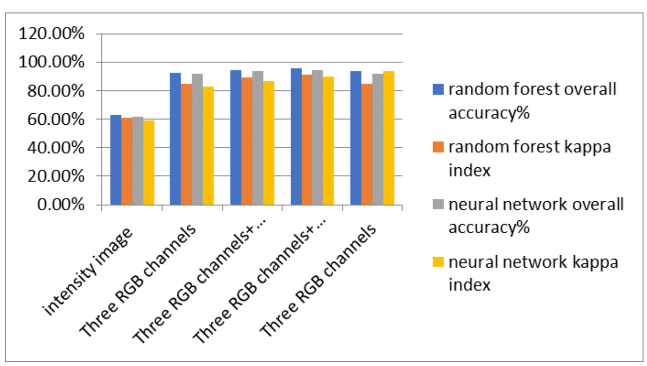

Figure 10. Overall Classification Accuracy and Kappa Coefficient for the Five Approaches of the two Classifiers

NNs are computational models inspired by the human brain. The multilayered feedforward NN has an input layer to receive inputs from sensors or other sources, an output layer to communicate with the outside world, and one or more hidden layers for data processing to transform the inputs into outputs. Each layer is made up of processing elements called neurons. Every neuron has a number of inputs, each of which must store a connection weight to indicate the strength of the connection. Connections are initially made with random weights. The neuron sums the weighted inputs and computes a single output using an activation function. A number of different activation functions can be used. Each neuron in a layer is fully connected to every neuron in the subsequent layer, forming a fully connected feedforward NN. In a feedforward NN, information flows from the input layer to the output layer without any feedback. Feedforward nets are guaranteed to reach stability and are faster than feedback nets (Packianather & Drake, 2005). In the present study, the Logistic activation function is used. Optimum parameters were determined as 0.9, 0.2, 0.9and 0.1 for training threshold contribution, training rate, training momentum, and training RMS exit criteria, respectively.

The Kappa coefficient measures the accuracy between classification results and reference data using the major diagonal and the chance agreement (Jensen, 2005). Table 1. shows the overall classification accuracy and Kappa coefficient for the five approaches of the random forest, Table 2. shows overall classification accuracy and Kappa coefficient for the five approaches of the neural network. The RMS plots of the neural network of the five cases were satisfied. The worst one was the RMS plot of the first case.

Table 1. Overall Classification Accuracy and Kappa Coefficient for the Five Approaches of the Random Forest

Feature	Random Forest Overall Accuracy (%)	Random Forest Kappa Index
Intensity image	63.2%	0.61
Three RGB channels	92.2%	0.85
Three RGB channels+ intensity	94.2%	0.89
Three RGB channels+ nDSM	95.9%	0.91
Three RGB channels+ Difference of returns	93.5%	0.85

Table 2. Overall Classification Accuracy and Kappa Coefficient for the Five Approaches of the Neural Network

Feature	Neural Network Overall Accuracy (%)	Neural Network Kappa Index
Intensity image	61.6%	0.59
Three RGB channels	91.7%	0.83
Three RGB channels+ intensity	93.5%	0.87
Three RGB channels+ nDSM	94.3%	0.90
Three RGB channels+ Difference of returns	92.1%	0.94

There are many factors that affect classification accuracy, especially with machine learning methods. One of the most crucial ones is the amount of training data. But getting enough training data can be very expensive or challenging, so finding other ways to increase prediction accuracy is necessary. In order to bridge the existing gap, this paper looks at the benefits of using five different LiDAR and RGB features to improve land cover mapping. It also evaluates the effectiveness of two machine learning algorithms, Random Forest (RF) and Artificial Neural Networks (ANNs), for land cover mapping of LiDAR and RGB images. Combining Lidar and RGB data, has overcome challenges related to the limits of active and passive remote sensing systems, providing promising results in land cover classification.

Random Forests (RF) classification was performed on Snap7 and Neural Networks (NN) classification was performed on ENVI5.1 using five different feature sets. Four types of land covers identified (urban, vegetation, road, and water) then the land cover classification was implemented with the existing data sets using five approaches.RGB was integrated with other ancillary data for improving the land cover classification accuracy. The contribution of the individual metrics has been evaluated. The novelty of this article is in the selection of the individual metrics combinations that used to improve land cover classification and evaluation of the use of two machine learning algorithms RF (ensample classifier) and NN.

The first segmentation was performed using the intensity image, the second segmentation was performed using the three RGB channels whereas the third segmentation was performed using the three RGB channels and intensity image. The fourth segmentation was performed using the three RGB channels and normalized digital surface model (nDSM). The last segmentation was performed using a combination of three RGB image channels and the difference of returns. The use of NN with LiDAR and RGB image classification appears more complex than statistical classifiers, because of the problems related to their design and implementation. The performance of an NN depends on its architecture and on the method of presenting the data and carrying out the training. The reason of using neural network classifier in LIDAR classification is that neural network use powerful learning algorithm that can give better classification result. Also Neural network classifier solves the mixed pixels problem and able to generalize.

There are many advantages of neural network classifier such as it does not require data that has normal distribution as maximum likelihood classifier does. Also neural network can integrate data from different sources such as data from geographic information system, which standard parametric classifier cannot work with. Neural network can also integrate multi sensor data types and complementary information content (object based information, texture and spectral information) in one classification process. However, their applicability has been challenged by the complexity of neural networks parameterization. The researchers noted that a neural network has great potential as a pattern recognition method for multi-source remotely sensed data because of the distribution-free nature of a neural network.

In the current research five different scheme were used with different attributes(features) such as normalized digital surface model (nDSM), the difference of returns, and the LiDAR intensity image with RGB image which require to modify the architecture of network to include these attributes in the input layer for each of the five classification performed with NN.

Quantitative accuracy assessments of the classification results were performed. Based on Table 1-2 and figure9 the overall accuracy and kappa statistics of the classification were calculated for the ten classifications that were performed with the five datasets. For the random forest, the overall accuracy of the first approach was 63.2%, and the kappa coefficient was 0.61, the overall accuracy of the second approach was 92.2%, and the kappa coefficient was 0.85, the overall accuracy of the third approach was 94.2%, and kappa coefficient was 0.89, the overall accuracy of the fourth approach was 95.9%, and kappa coefficient was 0.91, and the overall accuracy of the last approach was 97.5%, and kappa coefficient was 0.95. For the neural network, the overall accuracy of the first approach was 61.6%, and the kappa coefficient was 0.59, the overall accuracy of the second approach was 91.7%, and the kappa coefficient was 0.83, the overall accuracy of the third approach was 93.5%, and kappa coefficient was 0.87, the overall accuracy of the fourth approach was 94.3%, and kappa coefficient was 0.90, and the overall accuracy of the last approach was 96.7%, and kappa coefficient was 0.93.

From the results, we can see that the overall accuracies by using the radiometric component of LiDAR data, i.e. intensity alone are 63.2% and 61.6% for the random forest and neural network respectively. The errors in classification results may be due to the similarity in intensity values between land cover classes and intensity data has a certain level of noise, which may degrade the classification performance .While, the overall accuracy using three RGB channels 92.2%and 91.7% for the random forest and neural network respectively. One can attribute this to the spectral information (multispectral capability of RGB image). Meanwhile, by combining both three RGB channels+ intensity as the input images improved the results to %94.2 and %93.5 for the random forest and neural network respectively. Because of the LiDAR intensity data can contribute to the classification of shaded areas in urban environment, which can compensate such drawbacks induced by using high resolution digital aerial image. Furthermore, by combining both nDSM (which represents the above-ground feature only) and intensity data as the input images improved the results to 95.9% and %94.3 due to inclusion of height data from Light Detection and Ranging (LIDAR) data as an additional channel together with intensity.

The RMS plots of the neural network of the five cases were satisfied. The worst one was the RMS plot of the first case. Nevertheless, combining three RGB channels+ Difference of returns improve the overall accuracy of the classification results to 93.5% and 92.1% for the random forest and neural network respectively compared to the intensity image alone and three RGB channels alone. It was found that by adding Multi-cue to the three RGB channels, the classification results produced increase accuracy and more features were identified.

The results revealed also that the fourth approach is the best followed by the third approach then the last approach then the second approach followed by the first approach. The suggested approach significantly improves the accuracy of feature detection over approaches when only images and/or lidar data are used. It was found that the: (1) LiDAR intensity data is a very useful attribute for distinguishing between manmade and ground features; (2) LiDAR-derived height data is a very useful attribute for distinguishing elevated features (such as buildings, and trees) from ground features, where such a process cannot be achieved using color aerial photos only. Aerial image and airborne LiDAR data fusion can provide mutual benefits by compensating for each other's absence of 3D topography and multispectral information.

After that morphological operations were performed in order to remove noise. Morphological opening with a kernel size of 5×5 followed by morphological closing with a kernel size of 5×5 have been used utilizing ENVI 5.1 software intensity image only. According to this result, it can be deduced from the predictions that RF outperformed NN in classifying airborne LiDAR data and digital camera image. In addition, RF is more computationally effective as compared to NN. It was found also that random forest classification outperforms neural network classification in terms of classification accuracy one can attribute this due to random forest is ensample classifier and Neural network classification results mainly depends on the number of training samples, limiting the performance and accuracy when the training data set is insufficient for the learning algorithm.

The literature from the past has listed the advantages of the RF classification algorithm. For example, RF can process high dimensional data with low computational cost, low sensitivity to noise, small training sample sizes (Xie, 2023; Rodriguez-Galiano et al., 2012), and few overfitting or overtraining problems (Xie, 2023; Gislason et al., 2006). It can also combine high classification accuracy with great efficiency.

Xie, (2023); Rodriguez-Galiano & Chica-Rivas (2014), operated a land cover classification of a heterogeneous area with 14 categories by incorporating a suite of multitemporal Landsat images and digital terrain model (DTM) variables and RF algorithm. Results showed the superiority of RF over traditional single classifiers such as DT. In addition, RF not only provided a very high classification accuracy (0.92 in kappa), successfully generated and classified the most heterogeneous categories (e.g., shrublands) with 30% better accuracy, but it also ran efficiently on high-dimensional data and was able to more clearly differentiate between the different categories. Using Landsat-8 and Sentinal-2A, Loukika et al. (2021) found that RF is the best classifier among SVM, RF, and CART in terms of overall accuracy.

Christovam et al. (2019) made a comparison of three classification algorithms: Spectral Angle Mapper (SAM), Support Vector Machine (SVM) and Random Forest (RF) using hyperspectral imagery. The findings demonstrate that SVM and RF algorithms outperformed by far the SAM in terms of accuracy, and that the RF performing marginally better than the SVM. Tan et al. (2021), classified Landsat OLI-8 land use and land cover by comparing RF, ANN, and other classifiers. They discovered that RF performed better than ANN classifiers. Mishra et al. (2017) compared MLC, RF, SVM, and ANN in classifying Dual-polarimetric C-band SAR data and found that RF and SVM produced the best results. Yusof et al. (2021) found that ANN yielded the worst results in their research for evaluating SVM, SAM, and ANN for classifying Landsat-8 and Sentinel-2 imageries (Dixit & Agarwal, 2020). Ambinakudige & Intsiful (2022) implemented SVM and ANN using hyperspectral data , they found that SVM producing superior outcomes to ANN (Alshari et al.,2022).

Based on the results of the literature, we were able to confirm the superiority of the RF algorithm. Im et al. (2008) conducted a sensitive analysis on eight different LiDAR-derived surfaces for land cover classification on three different sites. It was found that the overall accuracy was increased by 10% to 20% when the intensity data was included in the feature spaces in their experiment (Yan et al., 2017). Based on the results of the literature, we were able to confirm that using different LiDAR-derived feature intended to increase the accuracy of land use land cover classification

4. Conclusion

This study aimed to improve land cover mapping from LIDAR data and RGB image using machine learning algorithms and multi-cue of LIDAR data and RGB image as input data. Also established a performance comparison between two supervised machine learning classifiers random forest (RF) and neural network (NN) for land cover classification of LIDAR data and RGB images. In this study, we sought to maximize the power of machine learning classification and LiDAR information by deriving features like the normalized surface model (nDSM), a difference of returns, and the LiDAR intensity image. RGB was integrated with other ancillary data for improving the land cover classification accuracy. The contribution of the individual metrics has been evaluated.

This paper attempts to fill the current void by examining the advantages of combining LiDAR and RGB images as a potent data source for enhancing land cover mapping through the use of five distinct LiDAR and RGB features, as well as compare the efficacy of two machine learning algorithms. Random Forest (RF) and Artificial Neural Networks (ANNs) for improving land cover mapping of LiDAR and RGB images. The results of the land cover classification show that the classification using individual band (Intensity) has an overall accuracy of **63.2**% and 61.6% for the random forest and neural network respectively.Then the classification with a combination of more bands (Multi-cue) improved the results of accuracy by approximately 30% compared with using individual band**.**

This proposed approach significantly improves the accuracy of feature detection over approaches when only images and/or lidar data are used**.** The results revealed also that the fourth approach is the best followed by the third approach then the last approach then the second approach followed by the first approach**.** It was found that the random forest classification gives better classification accuracy than neural network classification due to it is ensample classifier. It is recommended to use algorithms to remove noise in the processing of intensity images. Also, it is recommended to do additional research to use object-based classification.

In future work, we will extend the use of these algorithms to include 3D point cloud from LIDAR and stereo images , which should prevent loss of data and accuracy during the gridding process. We plan to combine the LIDAR point cloud with hyperspectral data to further improve land cover mapping accuracy. It would be simple to apply the suggested framework to other remote sensing data, such as LIDAR (unmanned aerial vehicle)UAV and UAV image data. Also it is suggested to integrate multisource data with additional machine learning and deep learning classification algorithms.

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