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Mapping LCLU Using Python Scripting

ABSTRACT:- *Land cover land use changes constantly with the time at local, regional, and global scales, therefore, remote sensing provides wide, and broad information for quantifying the location, extent, and variability of change; the reason and processes of change; and the responses to and consequences of change. And considering to the importance of mapping of (LCLU). For that reason this study will focus on the problems arising from the traditional classification (LCLU) that based on spatial resolution only which leads to prediction a thematic map with noisy classes, and using a new method that depend on spectral and spatial resolution to produce an acceptable classification and producing a thematic map with an acceptable database by using artificial neural network (ANN) and python in additional to other program. In this study the methods of classification were studied through using two images for the same study area , rapid eye image which has three spectral bands with high spatial resolution(5m) and Landsat 8 image (high spectral resolution with eight bands), also several programs like ENVI version 5.1, Arc GIS version 10.3, Python 3, and GPS. The result for this research was sensuousness as geometrics accuracy accepted in map production.*

Keywords:- *land use, land cover, artificial neural network, support vector machine*

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1. Introduction

Land cover refers to the physical and biological cover over the surface of the land, including water, vegetation, bare soil, and/or artificial structures. Land use is characterized by the arrangements, activities, and inputs relating to people in a certain land cover type to produce, change, or maintain it. Thus, both Land Cover and Land Use (LCLU) maps are beneficial for many geospatial applications such as change detection, natural disasters, urban planning, and site selection [1]. LCLU maps are often created by using remote sensing data with classification techniques. There are wide ranges of data that can be utilized for classification maps, these data can be grouped into airborne-based and satellite-based. The accurate classification methods are based on a sensor, spatial and spectral resolutions, optical or active [2]. The rapid eye image is one of the optical satellites and it has three spectral bands with high spatial resolution (5 m) [3]. Therefore, the captured data of Rapid Eye image has fine details of information about a study area. However, these data requests to robust image processing and classification technique for extracting the features. The classification techniques grouped into two methods such as pixel-based and object-based. The pixel-based method is a common classification. Several researchers were tried to combine the spectral and spatial information to produce a thematic map [4]. This method also allows the integration of multi-sensor data, such as rapid eye and Landsat. Considering these advantages, this study develops a pixel-based classification approach to produce a thematic map for the study area using rapid eye and Landsat satellite image. Land cover refers to the physical and biological cover over the surface of the land, including water, vegetation, bare soil, and/or artificial structures. Land use is characterized by the arrangements, activities, and inputs relating to people in a certain land cover type to produce, change, or maintain it. Thus, both Land Cover and Land Use (LCLU) maps are beneficial for many geospatial applications such as change detection, natural disasters, urban planning, and site selection [1]. LCLU maps are often created by using remote sensing data with classification techniques. There are wide ranges of data that can be utilized for classification maps, these data can be grouped into airborne-based and satellite-based. The accurate classification methods are based on a sensor, spatial and spectral resolutions, optical or active [2]. The rapid eye image is one of the optical satellites and it has three spectral bands with high spatial resolution (5 m) [3]. Therefore, the captured data of Rapid Eye image has fine details of information about a study area. However, these data requests to robust image processing and classification technique for extracting the features. The classification techniques grouped

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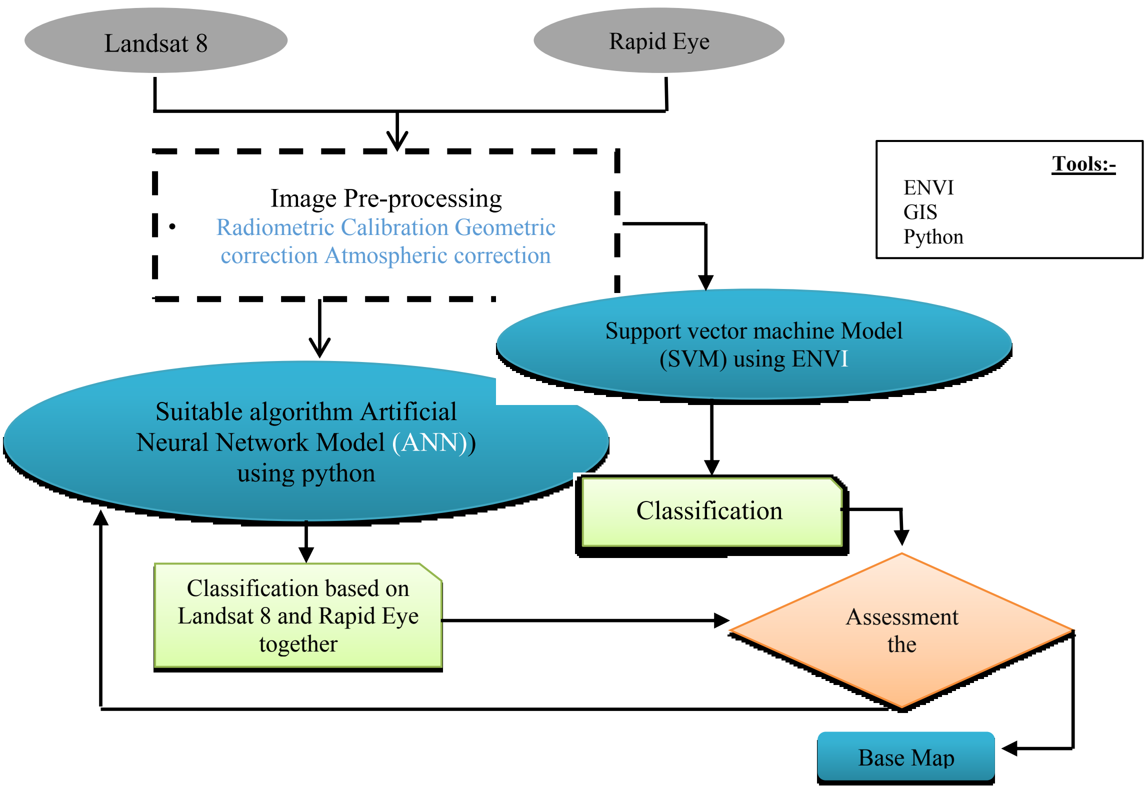
2. Problem Statement

Integration of different multispectral data can lead to an improved LCLU if proper classification methods are applied [5]. However, this integration also creates a challenge in regards to computing performance. Thus, many researchers have attempted to improve the traditional classification methods (e.g., maximum likelihood) [6]. Attempts were made to address the challenges above by selecting suitable algorithms to merge data from different sensors and then run a classification algorithm on the compressed data. This has resulted in better classification accuracies and better computing performances. However, still, the desired accuracies could not be achieved due to the limitations of the individual pixels. This study proposes a spatial-spectral feature extraction method based on ANN for image classification. It is expected that the proposed method to outperform other traditional technique while it is computing performance remains comparable to the traditional methods.

3. Methodology

In this research, datasets of Landsat and Rapid Eye images are going to be combined with proper spectral merging techniques such as neural networks. The spectral information of the image will be used using the reflectance values, while the spatial information will be extracted by a series of convolutional filters. Then, the combined features will be used to predict the label of each individual pixel in the area and produce an LCLU map. The final map then will be produced by post processing the created LCLU map in the previous step. Finally, a proper evaluation method will be applied to measure the improvements made by our method over other methods. As illustrated in the flowchart 1.



Flowchart 1: The sequence of operation

4. Research Objectives

The primary goal of this research is to production Land cover Land use for the study area based on ANN for image classification. The specific objectives are:

1. To develop a model based on ANN for image classification.
2. To compare the accuracy and computing performance of the proposed method with the traditional support vector machine and other methods.

5. Experimental Work

I. Study Area

This study is limited to the evaluation of LCLU in Karbala for future design and planning. The proposed model is easy-to-use engineering methods for image classification. In addition, the LCLU maps generated by ENVI, Python, and GIS can be available by which decision-makers can check the situations before and after the planning for the study area.

The research covers the area (25 km) in Karbala. In this study used two images: i) Rapid Eye image has three bands with 5 m panchromatic resolution and ii) Landsat 8 image has eight bands with 15 m panchromatic resolution. Used these data to acquire valuable information from the proposed model for producing LULC map. Artificial Neural Network (ANN) was utilized the proposed predicted model for Thematic map. As shown in Figure 1.

II. Significance of the Study

This study attempts to provide better insights into a pixel-based classification for multi-sensor data. It examines the advantages of integrating Landsat and Rapid Eye images to provid LCLU maps. It also analyzes some advanced classification methods such as ANN to analyze such datasets with less computation time. Overall, this study will improve the understanding of general users, urban planners, and decision-makers about generating LCLU maps from integrated remote sensing data.

III. Python

Python is an interpreted high-level programming language for general-purpose programming, created by Guido van Rossum and first released in 1991; Python has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales. In July 2018, Van Rossum stepped down as the leader in the language community after 30 years. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of Python's other implementations. Python and CPython are managed by the non-profit Python Software Foundation.

IV. Artificial Neural Network Model(ANN)

Neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by using electronic components or is simulated in software on a digital computer [7], it has several tasks such as classification, regression, clustering, Dimensionality reduction and others. These tasks depend on the desired output of a machine-learned system [8]. In general ANN Consists of (input, hidden, and output layers) that receive process and present the results [9] as shown in Figure 2.

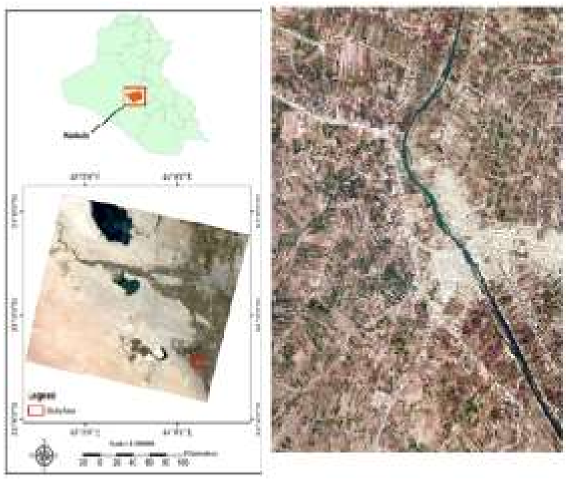


Figure 1: shows the area of study

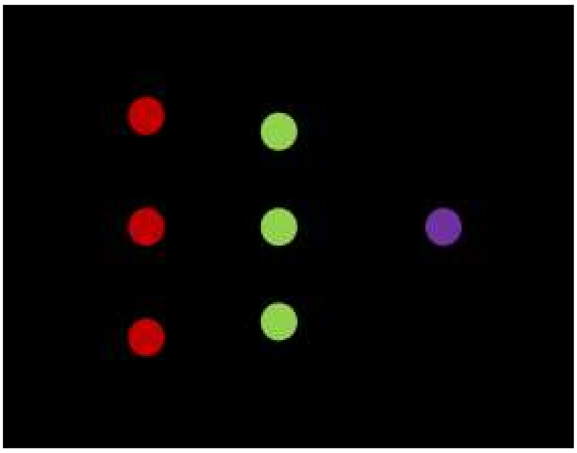


Figure 2: A simple structure of the neural network

ANN model has two equations, which are considered very important to improve the accuracy of the ANN model. First equation for minimizing the error function as illustrated in (Equation 1), the second equation for corrections to weight parameters such as computed and added to the previous values (Equation 2).

$$E = \frac{1}{2}\sum_{i=1}^{L}\left(d_j - o_j^M\right)^2 \qquad (1)$$

Where,
d_j Represents the desired output.
o_j^M Represents the current response of the node in the output layer.
L is the number of nodes in the output layer.

$$\begin{cases} \Delta w_{i,j} = -\mu \dfrac{\partial E}{\partial w_{i,j}} \\ \Delta w_{i,j}(t+1) = \Delta w_{i,j} + \alpha \Delta w_{i,j}(t) \end{cases} \qquad (2)$$

Where,
$w_{i,j}$ is weight parameter between node i
j, Δ represents a learning rate
α Represents a momentum factor t, the parameter α can be called smoothing or stabilizing factor as it smoothest the rapid changes between the weights [10].

V. Support Vector Machines model

Support Vector Machine (SVM) was first heard in 1992, Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression.

SVM is a statistical classification method that have m labeled training samples, $\{(\overrightarrow{x_i}, \overrightarrow{y_i} | \overrightarrow{x_i} \in R^n, y_i \in \{-1,1\}, i = 1 \ldots m$, SVM can generate a separation hyper surface with maximum generalization ability. Mathematically, the decision function can be formulated as follows:

$$d(\overrightarrow{x}) = \sum_{i=1}^{m} \alpha_i y_i K(\overrightarrow{x_i}, \overrightarrow{x}) + b \qquad (3)$$

Where α_i and b are the parameters determined by the SVM learning algorithm, and $K(\overrightarrow{x_i x})$ is the kernel function, which implicitly maps the samples to a high dimension space. The samples $\overrightarrow{x_i}$ with nonzero parameters α_i is called support vectors.

6. Process and Result Obtained from the Work Approach

Satellite Data that used in this study as shown in Table 1, the Landsat 8 image has eight spectral bands with 30 m spatial resolution which covered visible to near-infrared and one panchromatic band with a spatial resolution of 15 m [12], and Rapid Eye has three spectral bands with 5 m spatial resolution The spectral regions of bands are Blue (440-510 nm), Green (520-590 nm), Red (630-690 nm) [13]. Figure 3 illustrated the Landsat and rapid eye images. These two images are geo-referenced to follow the Universal Transverse Mercator projection (UTM Zone 38N) and the world geodetic system 1984 datum (WGS 1984). In addition, the images need to correct the radiometric correction and before the performance of the classification. Image Pre-processing Radiometric Calibration, Geometric correction, and Atmospheric correction using ENVI. Pan Sharpening algorithm was used to integrate the multispectral image (Landsat 8) with a high spatial resolution image (Rapid Eye) to acquire the improving visualization of urban and other features. As illustrated in Figure 4 the study area after these processes. Selecting the location of the samples. In this study was used geographic information system (GIS) to select these samples through create random point algorithm? This algorithm worked through identifies the boundary of the study area and select the sample percentage for the whole study area. After applying to create random points of the area, drawing the features and identify the type of features such as grass, building, water and others. As shown in Figure 5. Then using ARC GIS to convert Pan Sharpening image from raster to point, convert the point to the table. Classifying these tables in ANN using python program.

Table 1: Details of the datasets

Dataset	Date of Acquisition	Spatial Resolution	Spectral Resolution
Landsat	28/04/2013	15 m	7 bands

8	
Rapid Eye	28/04/2012
5 m	3 bands

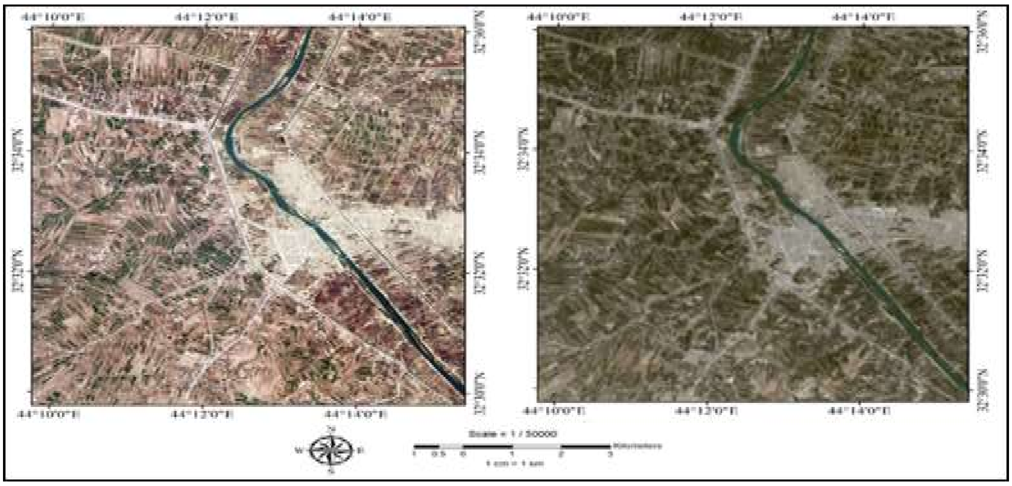
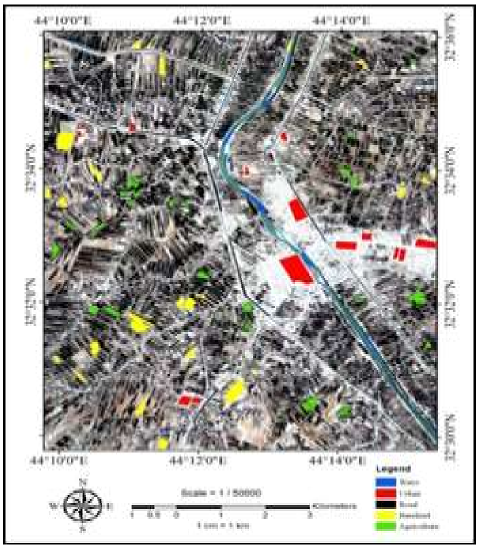


Figure 3: shows Rapid Eye image (left) and Landsat 8 image (right).



Figures 4: shows Sharpening image the Rapid Eye with Landsat images

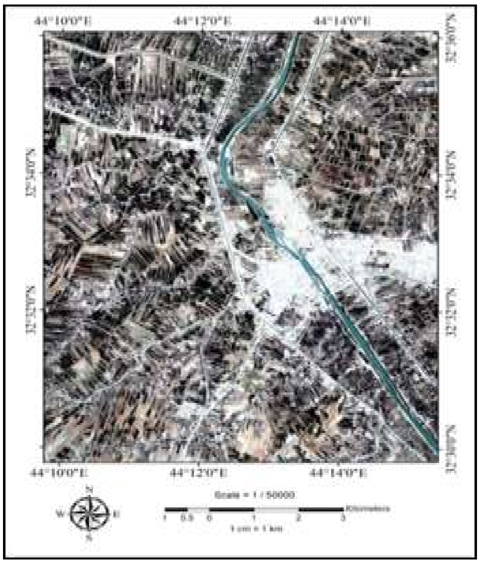


Figure 5: shows the samples for the study area.

I .Results of ANN

The Artificial Neural Network (ANN) was used with the best hyper parameters. This model was used to classify the combined image (the Landsat with Rapid Eye images) into five land cover classes such as urban, road, bare land, water, and agriculture. The overall accuracy and the kappa accuracy of the ANN model were found to be 0.983 and 0.976, respectively for on the training dataset. On the other hand, the accuracy of the testing dataset was 0.951 and 0.942 for overall accuracy and the kappa accuracy respectively.

II Result of SVM

In this study compared our work with another method like support vector machines (SVM). The SVM method with the best hyper parameters for these methods, the overall performance SVM model was about 0.91. Figure 6 shows the Rapid Eye, the sharpening images (Landsat with Rapid Eye images) and the classification maps of SVM and ANN classifiers. Regarding the classification map of SVM, the water, the roads, and the bare land classes are very noisy and are not clear. While the classification map of ANN classifier with sharpening image seems clearer and more logical. The results indicated firstly the ANN model is better than the SVM model as well as the multispectral image better than Rapid Eye image. The multispectral image is better because it has eight bands with high spatial resolution 5 meters. Nevertheless, the Rapid Eye image has three bands with high spatial resolution 5 meters. It is obvious the spectral band is very important for analysis to produce the Land use and land cover mapping besides the high spatial resolution.

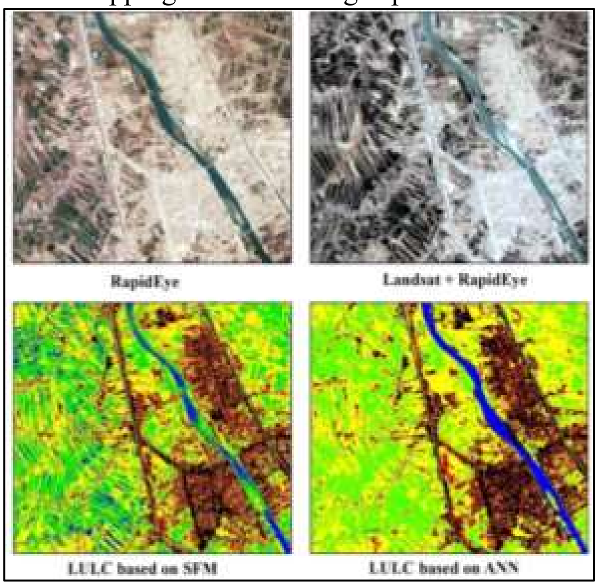


Figure 6: shows the classification maps produced from support vector Machines and Artificial Neural Network Model method.

III. Accuracy Assessment

In LCLU classification, accuracy assessment of the classification results is often required. The classification maps as created from remote sensing images may contain many errors due to many reasons including geometric error, complete atmospheric corrections, or due to indistinguishable classes. This is why accuracy assessment procedure is very important. Based on the confusion matrix analysis, the overall accuracy and a Kappa analysis were used to get the classification accuracy assessment. The overall accuracy was computed by dividing the total correct (some of the major diagonal) by the total number of pixels in the error matrix. However, the Kappa, which is a discrete multivariate technique used in accuracy assessments, which was computed as:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + x_{+i})}{N^2 - \sum_{i=1}^{r}(x_i + x_{+i})} \qquad (4)$$

Where r is the number of rows in the matrix, $x_{ii}$is the number of observations in row i and column i, x_i and x_{+i} are the marginal totals for row i and column i respectively and N is the total number of pixels.

In this research, the Accuracy Assessment for ANN& SVM are 0.97,and 0.91respectively. Table 2 shows the summary of the accuracy assessment for SVM and ANN methods.

Finally the accuracy assessments and sensitivity analysis of ANN Model

1. Network Analysis:-In this study was determined the hidden layers that affected the performance of network analysis depth. And also was checked several network depth ranging from 10 to 100 hidden layers. The evaluation of the ANN model was based on kappa accuracy and overall accuracy that was measured on training and testing datasets. The Table 3 was presented the summary of the results

Table 2: The accuracy of ANN and SVM classifiers

Classifier	Overall accuracy		kappa accuracy	
	Training	Testing	Training	Testing
ANN Model	0.974	0.954	0.959	0.936
SVM Model	0.917	0.884	0.873	0.851

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Table 3: Results of network depth analysis.

Experiment No.	Hidden Layers	Overall accuracy		kappa accuracy	
		Training	Testing	Training	Testing
1	10	0.661	0.623	0.522	0.485
2	15	0.681	0.623	0.632	0.545
3	25	0.693	0.635	0.644	0.557
4	40	0.711	0.653	0.662	0.575
5	60	0.753	0.694	0.701	0.635
6	75	0.798	0.771	0.783	0.758
7	85	0.852	0.837	0.809	0.784
8	95	0.896	0.876	0.834	0.814
9	100	0.974	0.954	0.959	0.936
10	105	0.861	0.846	0.814	0.807
11	110	0.807	0.793	0.787	0.769
12	120	0.694	0.669	0.658	0.608

2. Optimization Algorithm Analysis:- The optimizations of ANNs is very important because lead to improve the performance of the network model. There are many algorithms and several ways help to develop this network such as LBFGS, SGD and ADAM. Table 4 summarized the best accuracy, and the suitable algorithm for optimizing ANN classifier to classify the Sharpening image.

Table 4: Results of the optimization algorithm analysis.

Experiment No.	Solver	Overall accuracy		kappa accuracy	
		Training	Testing	Training	Testing
1	SGD	0.673	0.668	0.663	0.659
2	ADAM	0.872	0.856	0.839	0.828
3	**LBFGS**	**0.974**	**0.954**	**0.959**	**0.936**

3. Activation Function Analysis for ANN modeling:-Finally, the activation function was considered important for both the hidden and output layers because of this function influence on the overall performance of ANN modeling. The Tables 5 and 6 show the summary of the activation function analysis for hidden layers and output layers respectively

Table 5: Results of the activation function analysis for hidden layers.

Experiment No.	Activation	Overall accuracy		kappa accuracy	
		Training	Testing	Training	Testing
1	IDENTITY	0.841	0.829	0.806	0.792
2	LOGISTIC	0.761	0.753	0.742	0.735
3	**TANH**	**0.974**	**0.954**	**0.959**	**0.936**
4	RELU	0.898	0.884	0.867	0.853

Table 6: Results of the activation function analysis for output layers.

Experiment No.	Activation	Overall accuracy		kappa accuracy	
		Training	Testing	Training	Testing
1	IDENTITY	0.857	0.836	0.817	0.804
2	LOGISTIC	0.789	0.761	0.754	0.739
3	TANH	0.886	0.872	0.854	0.837
4	**RELU**	**0.974**	**0.954**	**0.959**	**0.936**

7. Conclusions

1. When compared the results of ANN model with results of SVM, the former model achieved high classification accuracies and the maps are more logical, it is mean the performance of ANN classifier outperforms the SVM method with best hyper parameters for these methods. The overall performance of the ANN model was about 0.97 while the SVM model was about 0.91, so this study suggests that the ANN model with these hyper parameters could significantly outperform the SVM model for Karbala area. As well as, regarding the classification map of the ANN model was more logical and better than the classification map of SVM.
2. The spectral band is very important for analysis to produce the Land use and land cover mapping besides the high spatial resolution.
3. The accuracy of the classification map was depended on the testing and training samples. The experiment number 9 with 100 hidden layers was achieved the best accuracy. On the training and testing, dataset the overall accuracy and kappa accuracy were 0.974, 0.954 and 0.959, 0.936 respectively. The results were indicated there are no specific patterns or number of hidden layer to improve the ANN model.
4. For Optimization, Algorithm Analysis found that the experiment number 3 with solver LBFGS was the suitable algorithm for land cover mapping, as well as the same classifier achieved the QA and K were 0.974, 0.954 and 0.959, 0.936 respectively.
5. In addition, for Activation Function Analysis for ANN modeling, this model analyzed several activation functions such as Logistic, RELU, identity and TANH. Therefore, the analysis of the ANN shows the best accuracy was achieved with TANH and, RELU for hidden layers and, output layers respectively, while the worst result of the ANN model was logistic activation function used.

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