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Employing Neural Networks Algorithm for LULC Mapping

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Abstract. Land use/land cover (LULC) maps represent a primary requirement for several geospatial applications around the world such as change detection, time series analysis, environment, and urban researches. Mapping LULC from remotely sensed data based on satellite image classification handle the rapid changes in extensive geographical areas. Several effective and efficient mechanisms suggested for supervised satellite image classification. The neural networks machine learning algorithm became a major method in supervised satellite image classification. The objective of this article is to employ neural networks as a machine learning algorithm for LULC mapping. The study applied in Ankara area, which is the capital city of Turkey. This work utilized a free Landsat 8 satellite image with the Operational Land Imager OLI sensor to implement the analysis. The image was obtained and processed in ArcGIS software. Then, the machine learning data set developed using Python scripting language. Every band out of 8 bands from Landsat 8 image considered as an explanatory variable, while the output variable defined based on visual interpretation. The training dataset built based on the signature file and random sample points. The training dataset divided into three sections, for training, for validation and the last section for testing. The training and testing processes were implemented using Google-Tensor Flow Keres library from Anaconda distribution. Feedforward neural network structure implemented with 500 neurons in the hidden layer. Confusion matrix used as accuracy assessment metrics to measure the performance of the developed model. The overall accuracy of the developed model was 92%. In terms of overall accuracy and robustness, the neural networks algorithm was effectively implemented and the LULC map produces. The model gained high accuracy that it is satisfied with the geospatial accuracy target. The consequence showed the competence of neural networks algorithm to generating LULC maps from Landsat 8 satellite images.

Keywords. Machine Learning, Neural Networks, Land Use/Land Cover (LULC), Satellite Image Classification.

1. Introduction

Land use land cover LULC mapping is an indispensable process for varied geospatial-relevant applications. LULC is the backbone data compulsory to perform the analysis in geospatial human activities and natural landscape (Abdullahi and Pradhan, 2018). LULC term separately defined as first, land use represents in what way land is utilized by humans. Second, the land cover represents the physical material covering the earth's surface comprising artificial surfaces built by human activities, soil, water and vegetation (Aydinoglu et al., 2010). In addition, LULC maps are a critical element affecting the spatial distributions of species (Saputra and Lee, 2019). Recently, satellite images have been extensively utilized to generate LULC data. Base on LULC data, several analyses performed for instance urban growth, the intensity of agricultural activities, deforestation, degradation level of wetlands, other human activities and predict their impacts on the landscape (Ikiel et al., 2012). Landsat satellite images represent a valuable data source to perform LULC mapping. The first satellite of Landsat series launched in 1972, while the last version is working until these days. Landsat satellite images are freely provided by the United State Geological Survey USGS with a medium spectral and spatial resolution (Hakkenberg et al., 2019).

Machine learning ML algorithms consider as the most modern and major method for mapping LULC. Neural networks NN is one of the main ML algorithms that gained robust performance in supervised satellite image classification area (Conforti et al., 2014; Dorofki et al., 2014; Huang et al., 2019; Jafar et al., 2010; Pelletier et al., 2019; Tayyebi et al., 2011). NN inspired and developed based on the process of biological cell (Jacobson, 2013; WEB, a). During the past years, a significant number of researches have been in the literature for mapping LULC using NN. Previous studies employed several NN structure and sub-algorithms to gain high classification performance (Pavel et al., 2008; Sun et al., 2019; Yi et al., 2019). Furthermore, the traditional NN algorithms gained good performance accuracy in generating LULC maps from satellite images (Wang et al., 2019). However, NN algorithms still need further improvement to gain high accuracy by adapting the most modern NN algorithms instead of conventional algorithms.

Therefore, the aim of this paper is to employ neural networks as a machine-learning algorithm for LULC mapping. This paper is adopting a free TensorFlow ML library for LULC mapping. TensorFlow is one of the most feasible and accessible solutions for artificial intelligence and machine learning. TensorFlow helps researchers by providing high-level programming libraries through Python. TensorFlow-Keras to provide fast NN experimentation and high performance (Liao et al., 2019).

2. Methods

This section discusses the content of the methods through the following sections: first, Study area and data collection. Second, satellite image Pre-processing. Third, neural networks training and testing. Finally, LULC post-processing.

2.1. Study area and data collection

The study area of this paper applied in the urban area of Ankara state in Turkey. The area is 122 km2 and has a population of over 5.4 million. Based on the study area and regional level of analysis, the study area mainly consisting of five LULC classes (Open areas, urban areas, green lands, roads and water bodies). The five classes clearly appear in the collected satellite image. The geographical location of the study area illustrated in Figure 1. Additionally, the figure presenting the Extend of the satellite image.

The satellite image obtained from USGS webs. The image gained from the Landsat 8 archive for the 2019 year. The image is 11 band produced by the Operational Land

Imager OLI sensor. Since the image is rich in spectral content, thus it helps the training stage to produce a high-performance NN classifier. The workflow of LULC mapping is presented in Figure 2.

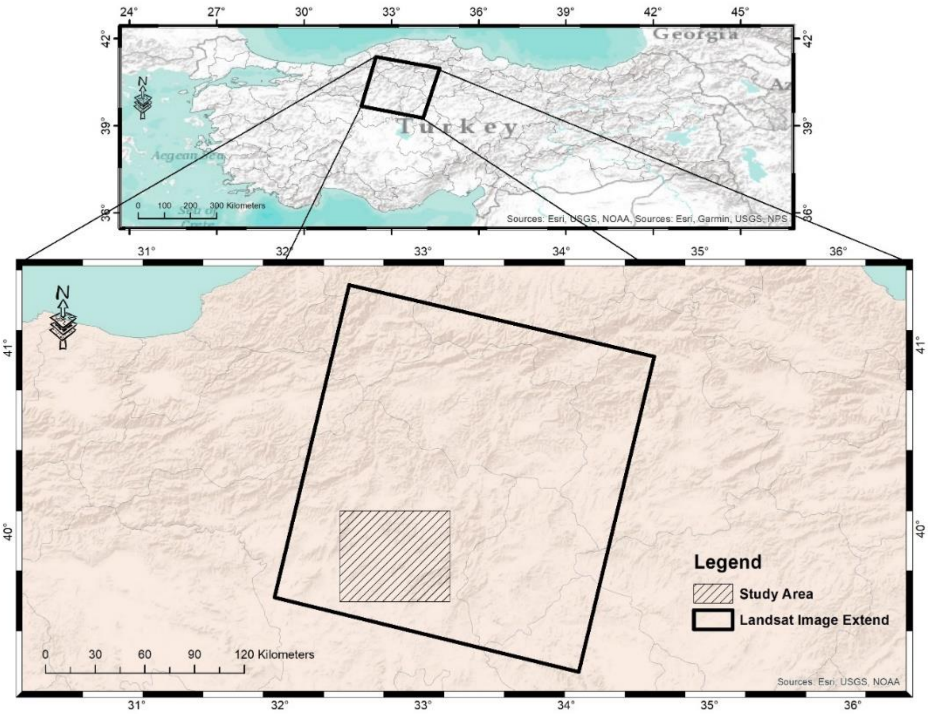

Figure 1. Study area Ankara-Turkey (Extend of Landsat satellite image in Ankara)

2.2. Satellite image Pre-processing

The Landsat satellite image subject to several pre-processing operations before developing the NN model such as unifying the cell size, masking the bands based on the study area border, unifying the number of rows and columns, and exclude the thermal bands. In addition, the sampling strategy relays on the Image classification toolbar in ArcMap software. The strategy is to draw some polygons for each LULC class and then convert these sets of polygons to a grid of points based on the pixel spatial resolution. The number of samples in this study for the training stage is 18050 points. Moreover, the 10 bands of the study area were reconstructed to produce the testing datasets for the full area. The 20 sub-datasets were generated. Mainly, the python scripting language utilized to apply the image pre-processing.

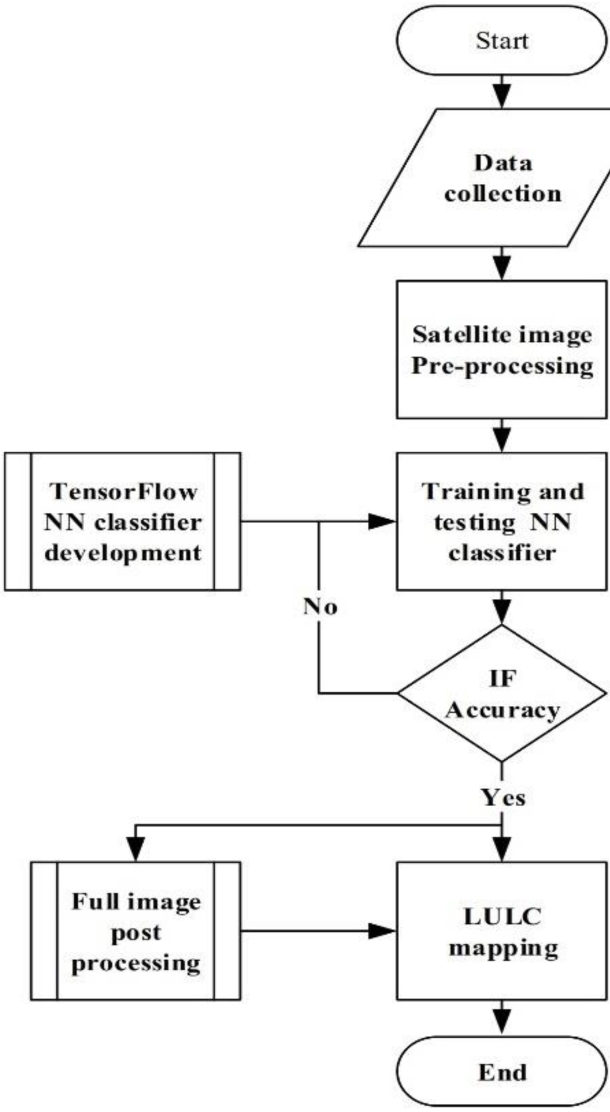

Figure 2. Workflow for LULC mapping

2.3. Neural networks training and testing

This stage is the main stage in this article. The training dataset used to develop the NN classifier. The classifier generated using Keras library in TensorFlow. The classifier developed using a feed-forward neural network structure. Classifier consisting of one input layer, two hidden layers (including 500 and 100 neurons respectively) and one output layer (consisting of 5 classes such as open areas, urban areas, green lands, roads and water bodies). According to the experimental results, the momentum-learning rate and performance accuracy monitored between the training and testing sets, then the best classifier with high accuracy and less error selected before entering the Overfitting zone.

The established model stored and used to classify the full satellite image. Confusion matrix metric employed to evaluate the performance accuracy of the classifier. Python pseudocode of the developed NN classifier presented in algorithm 1.

Algorithm 1. Pseudocode of developing NN classifier and mapping the LULC.

```
## Training stage
Read the input dataset
Divide the dataset to training and testing sets
Normalizing the datasets
Building the NN classifier structure and algorithms
Define NN classifier (inputs, hidden layers, outputs, and connections)

for j=1: number of neurons do
   Training the NN classifier using (j) neuron in the hidden layer
   Evaluating the performance accuracy of the classifier
   If the performance accuracy is satisfying the training parameters:
       Stope and save the final classifier
   Else:
       Continue the training process

## Testing stage
for h=1: number of chunks do
     read the chunk dataset
     using the trained NN classifier to classify (h) chunk dataset
     save the output classified values in TXT format
```

2.4. Datasets post processing and LULC mapping

In this section, the developed classifier with high-performance accuracy used to classify the full satellite image for Ankara area. The complete image consists of 2216 columns and 1837 rows. This size of the image considers a big size to be process for ML in a regular computer processor. This study employed the chunks method to divide and process the image. Blok by block, all the images transferred to the classifier and the classified values were stored in vector shape. Then, the output processed through python in ArcMap software to generate the final LULC map.

3. Results

This section consisting the outcomes of employment of neural networks algorithm for LULC mapping. The analysis applied in three stages, mainly pre-processing, NN training and LULC mapping. Landsat 8 image were the utilized data during the applications. The study area is Ankara area in Turkey. TensorFlow library employed to develop the NN classifier. The NN classifier trained until accomplished minimum error. The overall accuracy is 92% for training dataset based on confusion matrix metric, while overall accuracy is 89% for testing dataset. The optimal performance accuracy achieved after several experiments using different training functions or different number of neurons in the hidden layers. Figure 3 illustrating the performance accuracy of experiments according to different number of neurons (1 to 600 neurons in the first hidden layer). The ideal number achieved using 500 neurons in the first hidden layer and 100 neurons in the second hidden layer. Based on 10 bands, NN easily gained high performance accuracy in limited training time.

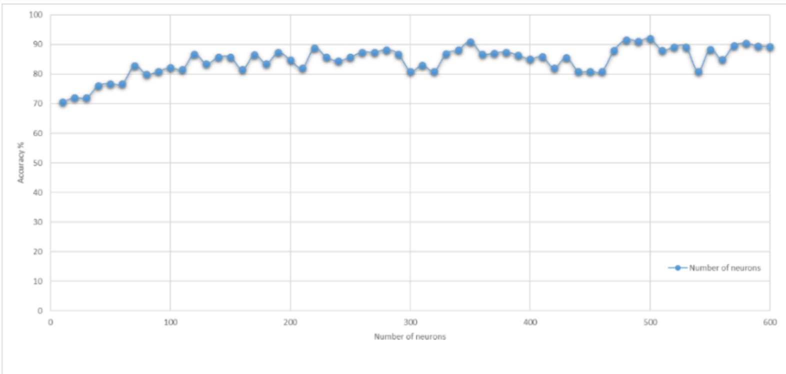

Figure 3. Performance accuracy of experiments according to different number of neurons.

In addition, the performance accuracy of each class evaluated using the precision and recall metrics. The outcomes illustrated in **Figure 4**. The precision rates of classes are as following: open areas (99.3%), urban areas (83.2%), green lands (98.8%), roads (95.1%) and water bodies (87.1%). The recall rates of classes are as following: open areas (93.3%), urban areas (92.3%), green lands (91.2%), roads (91.7%) and water bodies (72.2). In general, the performance accuracy of NN classifier is high in the classes that have a wide area compere with low performance in classes with small areas. According to the regional level of analysis, the performance of the classifier is quite good.

Furthermore, the true positive classified values across the five LULC classes showing high-performance accuracy. The true positive rate presenting the values that correctly classified with referencing to the original target data. The true positive rate of open areas (16.6%), urban areas (26.4%), green lands (1.3%), roads (95.1%) and water bodies (1.1%).

Finally, the classified values processed in ArcGIS software and LULC map produced. The generated LULC map demonstrated in Figure 5. The LULC map consisting of 5 classes. The open areas occupy the highest percentage of the total area (86%). The urban areas represent 9.15% and green lands 3.69%. The roads represent 0.37%, while water bodies represent the minimum areas 0.31%.

Output Class \ Target Class	1	2	3	4	5	
1	**2988** 16.6%	**0** 0.0%	**0** 0.0%	**4** 0.0%	**17** 0.1%	99.3% 0.7%
2	**213** 1.2%	**4766** 26.4%	**22** 0.1%	**724** 4.0%	**4** 0.0%	83.2% 16.8%
3	**0** 0.0%	**3** 0.0%	**239** 1.3%	**0** 0.0%	**0** 0.0%	98.8% 1.2%
4	**0** 0.0%	**371** 2.1%	**1** 0.0%	**8408** 46.6%	**57** 0.3%	95.1% 4.9%
5	**0** 0.0%	**0** 0.0%	**0** 0.0%	**30** 0.2%	**203** 1.1%	87.1% 12.9%
	93.3% 6.7%	92.7% 7.3%	91.2% 8.8%	91.7% 8.3%	72.2% 27.8%	**92.0% 8.0%**

Figure 4. Performance evaluation using overall accuracy, precision and recall metrics.

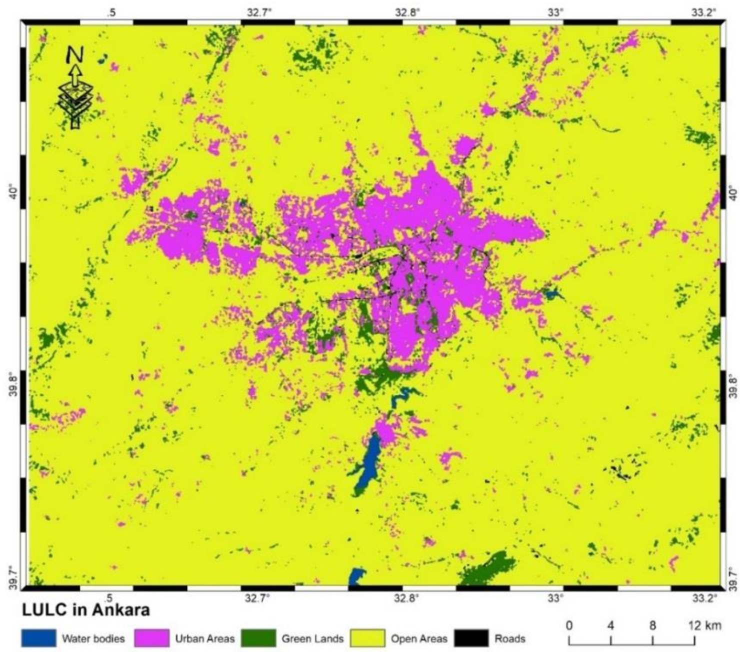

Figure 5. LULC map (map used classifier to classify Landsat 8 image based on NN and TensorFlow)

4. Conclusion

During recent decades, due to the massive size of available remote sensing satellite images, a great need released to develop the machine learning classifiers. The classifiers replace the manual and fatigued digitizing process. In addition, the need to develop the performance accuracy of classifiers is high. The objective of this article is to employ neural networks as a machine-learning algorithm for LULC mapping.

In this paper, the Landsat 8 image collected and processed in ArcGIS. Ankara area in Turkey selected as a study area to implement the analysis. TensorFlow ML library in Python programming language used to develop the classifier. Feedforward neural network structure utilized in the classifier development stage. Around 18050 sample points used as to generate the training dataset. Based on several experiments, the developed classifier gained 92% overall accuracy. In general, the overall accuracy is increasing equally to the increase in the number of neurons in the first hidden layer. The precision rates of each class calculated for open areas (99.3%), urban areas (83.2%), green lands (98.8%), roads (95.1%) and water bodies (87.1%). The results proving the ability of the NN classifier across the multi classes of LULC.

To conclude, the outcomes show that the usage of the NN classifier has successfully implemented LULC mapping from Landsat 8 satellite images in a reasonable time with high-performance accuracy. The NN classifier can be employed in regional and environmental research to classifying the multispectral satellite images. The powerful TensorFlow platform as ML library is highly recommended to develop the NN classifiers for LULC mapping. The NN classifiers can produce LULC maps in a short time with satisfying results.

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References

Abdullahi, S., Pradhan, B. (2018). Land Use Change Modeling and the Effect of Compact City Paradigms: Integration of GIS-Based Cellular Automata and Weights-of-Evidence Techniques. *Environmental Earth Sciences*, 77(6):251.

Aydinoglu, A. C., Yomralioglu, T., Inan, H. I., Sesli, F. A. (2010). Managing Land Use / Cover Data Harmonized to Support Land Administration and Environmental Applications in Turkey. *Scientific Research and Essays,* 5(3):275–84.

Conforti, M., Pascale, S., Robustelli, G., Sdao, F. (2014). Evaluation of Prediction Capability of the Artificial Neural Networks for Mapping Landslide Susceptibility in the Turbolo River Catchment (Northern Calabria, Italy). *Catena,* 113(0):236–50.

Dorofki, M., Elshafie, A. H., Jaafar, O., Karim, O. A., Abdullah, S. (2014). A GIS-ANN-Based Approach for Enhancing the Effect of Slope in the Modified Green-Ampt Model. *Water Resources Management,* 28(2):391–406.

Hakkenberg, C. R., Dannenberg, M. P., Song, C., Ensor, K. B. (2019). Characterizing Multi-Decadal, Annual Land Cover Change Dynamics in Houston, TX Based on Automated Classification of Landsat Imagery. *International Journal of Remote Sensing,* 40(2):693–718.

Huang, J., Zhang, X., Xin, Q., Sun, Y., Zhang, P. (2019). Automatic Building Extraction from High-Resolution Aerial Images and LiDAR Data Using Gated Residual Refinement Network. *ISPRS Journal of Photogrammetry and Remote Sensing,* 151:91–105.

Ikiel, C., Dutucu, A. A., Ustaoglu, B., Kilic, D. E. (2012). Land Use and Land Cover (LULC) Classification Using Spot-5 Image in the Adapazari Plain and Its Surroundings, Turkey. *TOJSAT 2,* (2):37–42.

Jacobson, L. (2013). Introduction to Artificial Neural Networks - Part 1. The Project Spot. 19,1, 2017, (http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-1/7).

Jafar, R., Shahrour, I., Juran, I. (2010). Application of Artificial Neural Networks (ANN) to Model the Failure of Urban Water Mains. *Mathematical and Computer Modelling,* 51(9–10):1170–80.

Liao, W., Anthony, P., Parrett, L., Guzide, O. (2019). Artificial Intelligence and Deep Learning with Tensorflow. *Proceedings of the West Virginia Academy of Science,* 91(1).

Pavel, M., Fannin, J., Nelson, J. D. (2008). Replication of a Terrain Stability Mapping Using an Artificial Neural Network. *Geomorphology,* 97(3–4):356–73.

Pelletier, C., Webb, G. I., Petitjean, F. (2019). Temporal Convolutional Neural Network for the Classification of Satellite Image Time Series. *Remote Sensing,* 11(5):523.

Saputra, H., Han, L. (2019). Prediction of Land Use and Land Cover Changes for North Sumatra, Indonesia, Using an Artificial-Neural-Network-Based Cellular Automaton. *Sustainability,* 11(11):3024.

Sun, G., Huang, H., Zhang, A., Li, F., Zhao, H., Fu, H.. (2019). Fusion of Multiscale Convolutional Neural Networks for Building Extraction in Very High-Resolution Images. *Remote Sensing,* 11(3).

Tayyebi, A., Pijanowski, B. C., Tayyebbi, A. H. (2011). An Urban Growth Boundary Model Using Neural Networks, GIS and Radial Parameterization: An Application to Tehran, Iran. *Landscape and Urban Planning,* 100(1–2):35–44.

Wang, L., Jia, Y., Yao, Y., Xu, D.. (2019). Accuracy Assessment of Land Use Classification Using Support Vector Machine and Neural Network for Coal Mining Area of Hegang City, China. *Nature Environment and Pollution Technology,* 18(1):335–41.

Yi, Y., Zhang, Z., Zhang, W., Zhang, C., Li, W., Zhao, T. (2019). Semantic Segmentation of Urban Buildings from VHR Remote Sensing Imagery Using a Deep Convolutional Neural Network. *Remote Sensing,* 11(15).

WEB (a). Neuralpower. An Overview of Neural Networks. http://www.neuralpower.com/technology.

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