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Determination of vineyards with support vector machine and deep learning-based Image classification

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ABSTRACT

The study aims to determine the spatial distribution of vineyards with support vector machines (SVM) and convolutional neural network (CNN) based deep learning model. Multispectral (MS) and Panchromatic (PAN) bands of the high spatial resolution Worldview-2 (WV-2) satellite image were used for the study area located in Erzincan Üzümlü district. MS and PAN bands were fused to enhance the spatial resolution of the WV-2 multispectral image, making the vineyards more distinct and visible. Then, training samples were collected for five predetermined classes (vineyard, forest, soil, road and shadow) within the boundaries of the study area to generate training and test data, and the satellite image was classified using both Support Vector Machine (SVM) and CNN algorithms. Classification results were investigated using error matrices, kappa analyzes, and Mcnemar tests. As a result of the accuracy analysis, general classification accuracies and kappa values for CNN and SVM were obtained as 86.00% (0.8536) and 63.33% (0.6077), respectively. It has been observed that the CNN classifier provides higher classification accuracy (24% higher than the SVM). In addition, it was examined whether the differences between the McNemar test and the classification results were significant or not. As a result of the McNemar test for CNN and SVM, a value of 10.298 χ^2 was calculated. The fact that the calculated χ^2 value is greater than 3.84 reveals that the CNN classifier significantly increases the classification accuracy at the 95% confidence interval.

1. Introduction

Remote sensing techniques and satellite images make great contributions in many areas such as the detection, tracking, protection of agricultural products, environmental and urban applications. Image classification is used in many different areas such as monitoring tropical forests (Christian ve Krishnayya 2009), which are of great importance in terms of being a rich natural resource with biological diversity, monitoring of coastal change (Gungor et al. 2010), monitoring of urban development (Chi et al. 2009), object extraction (Zhang et al. 2007), classification of land cover (Huang et al. 2011) and classification of product types (Sun and Di 2020). Image classification, also called information extraction, is the process of transforming this information into meaningful land cover information by using the pixel values in an image (Gao 2009). Image classification algorithms in remote sensing have been developed to meet the needs of various applications. In recent years, different learning-based algorithms have been developed for classification in order to quickly extract the most accurate and reliable information from satellite images. Commonly used learning-based classifiers include Random Forest, Bagging, Boosting, Decision Trees, Artificial Neural Networks, Support Vector Machines and K-Nearest Neighbor. These algorithms are also called machine learning methods. Machine learning methods using large enough data and parameters can automatically infer rules and constraints that users cannot see/notice directly. These methods try to find the most suitable model for the new data with the decision rules created with the training and test data. In addition, in recent years, deep learning algorithms, which are a sub-branch of machine learning methods, have been widely used for more accurate and reliable determination of agricultural products in precision agriculture applications. For

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example, Grinblat et al. (2016) used deep learning algorithms to recognize plants from the vascular structures of plants and identified plants with high accuracy. Ferentinos et al. (2018) used deep learning algorithms to detect diseased plants. They detected the diseased ones on 25 different plant species with 99.53% accuracy. Chlingarian et al. (2018) made product yield predictions with deep learning algorithms. In addition, they defined plant species by classifying images with 99.58% accuracy with deep learning algorithms (Abdullahi et al. 2017). As can be seen from the studies, various satellite images and methods are used in the determination of agricultural products. It will be possible to detect agricultural products in a shorter time and accurately with the methods and satellite images selected according to the characteristics of the study area and the product. Cimin grape, which has economic value, is an endemic variety grown in the Üzümlü region. This study aims to determine the distribution of the cultivation areas of Cimin grape using satellite images.

1.1. Study area and dataset

An area of 25 hectares in Üzümlü district, where the Cimin, or Üzümlü grape, which is described as the Erzincan grape is grown, was determined as the pilot study area (Figure 1). Üzümlü District is located in the Upper Euphrates Section of the Eastern Anatolia Region, within the borders of Erzincan Province. A large part of the district land (80%) is located in the Öz Mountains (approximately 3500 m altitude.) region extending to the north of the Erzincan basin, and a small part (20%) is located in the Erzincan plain (approximately 1200 m altitude). Üzümlü (410 km2) is the second smallest district of Erzincan province after Otlukbeli (254 km2) in terms of area size (TR Erzincan Governorship, 2021).

The Worldview-2 (WV-2) satellite image used in the study has 8 MS bands (Coastal, Blue, Green, Yellow, Red, Red Edge, Near-Infrared 1, NearInfrared 2) with a spatial resolution of 2 m and a panchromatic band with a spatial resolution of 0.5 m. Radiometric, atmospheric and geometric corrections of this image used in the study were made by the company from which the satellite image was taken.

2. Method

The study includes accurate and reliable determination of grape fields using two widely used machine learning methods, Support Vector Machine (SVM) and convolutional neural network (CNN). In the study, the WV-2 MS and PAN images were fused using the Hyperspherical Color Space (HCS) pan sharpening method to discern the grape areas more clearly in the image. The HCS is a method developed for the Worldview-2 images (Padwick 2010), and there are various articles in the literature supporting that the HCS image fusion method gives successful results in terms of spectral and spatial aspects (Akar 2019; Li et al. 2015; Padwick et al. 2010; Anshu et al. 2017). For this reason, the HCS method was preferred in this study. Then, training pixels were collected in ENVI software for five classes (vineyard, forest, soil, road, shadow) over the fused image. A total of 70505 pixels were collected. Using this training data, the image was classified using SVM and CNN algorithms. Python programming language were used to classify the image with CNN. Optimum parameters for the image in classification were determined by a trial and error approach. The classification methods used for this study are explained theoretically below.

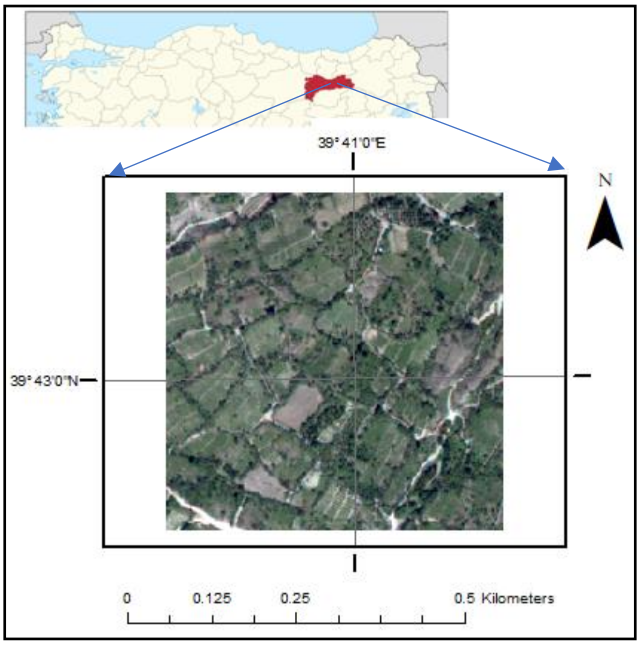


Figure 1. Study area

2.1. Support vector machine

The Support Vector Machine (SVM) classifier can classify data that is both linearly separable and nonlinearly separable. The aim is to determine the optimum hyperplane that separates the classes from each other (Vapnik 1995). If the classes are linearly separable from each other, it determines the planes with the greatest distance from the planes separating the classes from each other and uses these planes to create a linear discriminating function. Classes are separated by linear functions. If these classes cannot be separated linearly, they are moved to another higher-dimensional space where the classes can be separated linearly by using a positive C parameter and kernel functions that will minimize the classification error and maximize the distance between the planes. Classification takes place in this space (Özkan 2008; (Tso and Mather 2009; Stephens and Diesing 2014, Çölkesen and Yomralıoğlu 2014) The most widely used kernel function is the Radial basis function since it performs well (Thanh Noi and Kappas 2018); Kavzoglu and Çölkesen 2009).

2.2. Deep learning

Deep learning, which is usually characterized by neural networks containing more than two hidden layers, is recognized as one of the ten breakthrough technologies of 2013 (Zhu et al. 2017). The deep learning model created in this study is based on the structure of convolutional neural networks. Convolutional neural networks (CNN), which are effectively used in image operations, are also successful in classifying satellite images (Saralioglu and Gungor 2020).

In the model created in this study, four 3D convolution layers were used. The filter size of each layer was set to be 3x3. The filter numbers were created as 128 in the first layer, 64 in the second layer, 32 in the third layer, and 16 in the 4th layer. After the convolution layers, two fully connected layers were used. The first is a dense layer that makes a rough classification of the features extracted by the convolutional layer. The second is the last layer in the model and is used with a Softmax classifier that extracts the class scores. The Softmax classifier produces values between 0 and 1 for each class and ensures that the class with the highest score is evaluated correctly. Parametric Rectified Linear Unit (PReLU) as activation function, Adam as optimization method, and categorical cross-entropy as subduction function was used in the model. The total number of parameters in the created deep learning model is 3118405.

3. Results and discussion

The accuracy of the thematic images (Figure 2) obtained as a result of the classification of the image with the SVM and CNN algorithms were examined with error matrices. In the accuracy analysis with error matrices, a total of 150 random points were scattered on the image proportionally to the area occupied by each class. When the overall classification accuracies produced from the error matrices were examined, the CNN method classified the image with an accuracy of 86.00% and the SVM method with an accuracy of 63.33% (Table 1). Accordingly, it is seen that the CNN method classifies the image 23% better. Calculated Kappa values also support this result.

Table 1. Overall classification accuracies and kappa analysis

	Overall Accuracy	Cohen's kappa
CNN	86.00	0.8536
SVM	63.33	0.6077

In addition, the success of these methods for each class was also examined by the Producer's (PA) and User's (UA) accuracies (Figure 3). According to Figure 3, in terms of PA, forest, road and shadow classes were classified 8%, 67% and 54% better, respectively, by the CNN method. According to UA, the CNN method was 22% more successful than SVM in vineyard class, 24% in forest class and 27% in soil class. In general, CNN method performed better than SVM. When the error matrices were examined, it was observed that the spectral characteristics of the forest and vineyard classes were very similar causing the most confusion among all classes. Similarly, granular stabilized roads in the Road class, very dark pixels in the Soil class and Forest class have similar spectral characteristics with the shadow class, resulting in incorrect classification results. SVM was not as successful as CNN in classifying these classes.

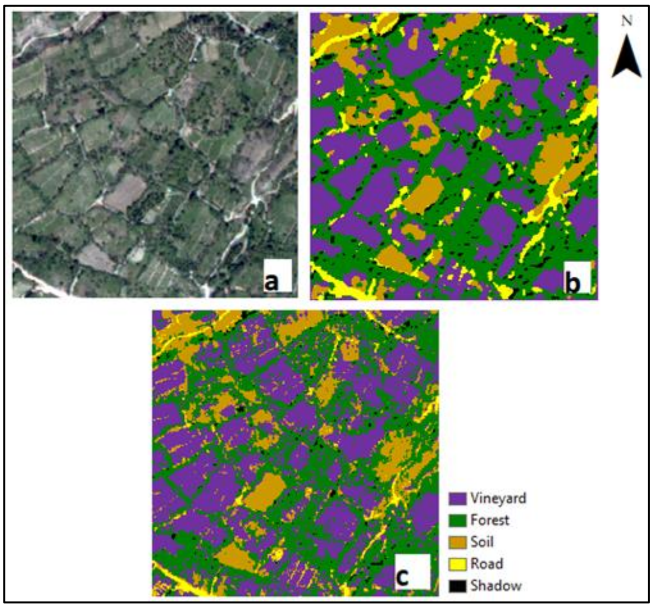
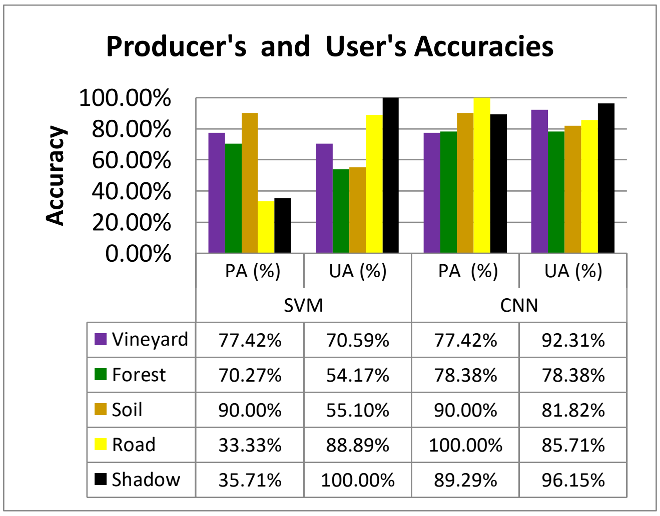


Figure 2. a) Fused image, b) Thematic images obtained from CNN, c) Thematic image obtained from SVM

In addition, it was examined whether the differences between the McNemar test and the classification results were significant. As a result of the McNemar test for CNN and SVM, the value of 10.298 χ^2 was calculated (Table 2). The fact that the calculated χ^2 value is greater than 3.84 reveals that the CNN classifier significantly increases accuracy in the 95% confidence interval in the classification process.



	SVM PA (%)	SVM UA (%)	CNN PA (%)	CNN UA (%)
Vineyard	77.42%	70.59%	77.42%	92.31%
Forest	70.27%	54.17%	78.38%	78.38%
Soil	90.00%	55.10%	90.00%	81.82%
Road	33.33%	88.89%	100.00%	85.71%
Shadow	35.71%	100.00%	89.29%	96.15%

Figure 3. Producer's and User's Accuracies

Table 2. Assessment of the significance of the difference between CNN and SVM with McNemar test

	f_{11}	f_{12}	f_{21}	f_{22}	Total	χ^2
CNN-SVM	65	35	12	38	150	10.298

f_{11} : The number of samples that both methods can correctly classify, f_{22}: The number of samples that both methods cannot classify correctly, f_{12}: The number of samples misclassified by method 1 but correctly classifiedby method 2,f_{21}: The number of samples misclassified by method 2 but correctly classified by method 1.

4. Conclusion

In the study, it is aimed to determine the spatial distribution of the vineyards with the SVM and CNN algorithms, which are the most widely used machine learning approaches. As a result of the analysis, the CNN method classified the specified study area with an accuracy of 86.00% and the SVM with an accuracy of 63.33%. Accordingly, the CNN method showed 23% better classification performance than SVM and classified the spatial distribution of the vineyards more accurately. Kappa analyzes also support this result. In addition, the fact that the χ^2 value, which was calculated as 10.298 with the McNemar test, was greater than 3.84, shows that the results obtained from these two methods are significant and the performances of these two methods are different. As a result, the CNN method performed better than SVM in the classification of vineyards, which are agricultural products.

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