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Evaluating the performance of object-based machine learning and deep learning models in classifying different maize genotypes with multispectral UAV imagery

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Abstract

Modern remote sensing technologies play a critical role in agricultural applications, especially in recent years with the advances in unmanned aerial vehicle (UAV) technologies and artificial intelligence. Remotely sensed imagery is an invaluable data source for sustainable agricultural activities, such as precision agriculture. This study evaluates a comparative analysis of the performance of machine learning (ML) and deep learning models in classifying 12 different maize genotopies from multispectral UAV images. In this context, ortho mosaic and canopy height model obtained from UAV-mounted multispectral camera of the study area in Kirazca Agricultural Enterprise located in Arifiye district of Sakarya province were used as a main dataset. The object-based classification results show that the overall accuracy (OA) of the crop maps produced with the Rotation Forest (RotFor) and Canonical Correlation Forest algorithms was approximately 80%, while the OA value was 74.18% for Support Vector Machine algorithm. On the other hand, the popular U-Net model outperformed the ML-based models with an OA value of 97.61%. Individual class accuracy analyses revealed that the RotFor algorithm attained F-score values exceeding 90% for only 2 maize genotypes (i.e., Com. Sw. and Com. Ar.), whereas F-score values calculated with the U-Net model surpassed 95% for all 12 genotypes.

Introduction

The cereal group, providing more energy to billions than all other crops combined, is grown in large quantities across the Earth [1]. Maize is characterized by high yields and adaptability to changing conditions [2]. About 65-70% of global maize production is used for animal feed, 20% for human consumption, and 10-15% for industry [3]. The increasing global population has raised maize demand, leading to the consideration of imports for production balance [4]. Monitoring the status of cultivated maize fields is crucial for assessing crop health, optimizing agricultural practices, and ensuring timely interventions to enhance yield and sustainability. Traditional field-observation based methods in plant monitoring depends on labor-intensive and expensive methods. In contrast, modern remote sensing technologies, offering accessible, highly accurate, and cost-effective data, have been recently used effectively in crop monitoring applications. With technological advancements in recent years, unmanned aerial vehicles (UAVs) equipped with multispectral (MS) and hyperspectral sensors can provide cost-effective data at high spatial, spectral, temporal resolutions [5]. The timely acquired data is utilized in various smart agriculture applications, including crop health monitoring, weed or pesticide detection, water content estimation, crop quality assessment, and crop mapping using machine learning (ML) algorithms. In the remote sensing literature, studies on detecting crop species and genotypes are mainly based on image classification. For example, utilizing UAV MS images, Li et al. (2021) detected maize-cultivated areas. Employing an object-based image classification approach with Support Vector Machine (SVM) (achieving an accuracy of 90.27%) and Random Forest (achieving an accuracy of 92.36%). ML algorithms, the cultivated areas were determined as 96.54 and 98.77 hectares, respectively [6]. On the other hand, in another study where UAV images were used as the primary data set, U-Net based models were used to separate maize crops. The results showed approximately 48% better classification performance than the ML algorithm [7]. Furthermore, Colkesen et al. (2023) utilized deep learning (DL) techniques for the classification of the UAV image dataset and achieved high accuracy in detecting and counting poplar tree crown structures (F-Score: 88.20%) [8].

Study Area and Dataset

Study area is located in Kirazca agricultural enterprise of Sakarya Maize Research Institute in Arifiye district of Sakarya province, Türkiye (Figure 1). In the field, 12 maize genotypes have been cultivated in parcels designed as rectangles measuring 500m^2 (20 m x 25 m) each. MS orthomosaic dataset obtained on July 19, 2022, from a DJI Phantom 4 UAV equipped with a five-channel multispectral camera (Red, Green, Blue, Red edge, and Near Infrared) was employed to map various maize genotypes in cultivated fields during the tassel growth stage. Aerial photographs were acquired at a flight altitude of 50m with 80% forward and 60% side overlap, and orthomosaics with a Ground Sampling Distance of 2.7cm and 16-bit resolution were produced using the structure-from-motion (SfM)-based image matching software Agisoft Metashape Professional. In addition plant heights, called Canopy Height Model (CHM), were calculated with the help of pixel differences between Digital Surface Model and Digital Terrain Model produced based on DJI Phantom 4 v2 RGB UAV [9]. CHM was added as a band to the original spectral variables to create a dataset to improve image classification accuracy.

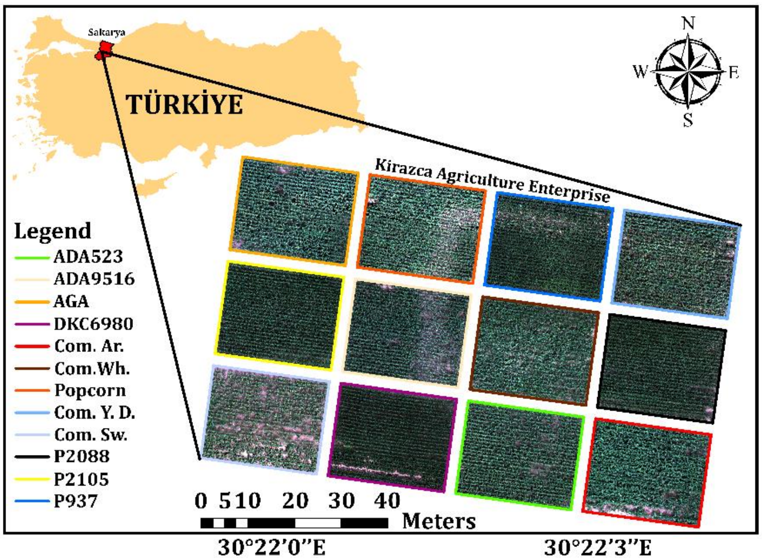

Figure 1. Study area

Methodology

In this study, state-of-the art ML algorithms such as SVM, RotFor, and CCF, as well as a well-known DL network, U-Net, were employed to produce a crop map representing 12 maize genotypes using the MS orthomosaic dataset. Object-based classification consists of three stages: image segmentation, class labeling using ML algorithms and accuracy assessment. Image segmentation was performed using the MRS algorithm in eCognition 9 software [10], which is managed by three important parameters such as scale (S), shape (Sh) and compactness (C). Sh and C were determined by trial and error and S was determined automatically based on the ESP-2 tool developed by [11]. SVM algorithm, originally developed to separate two classes [12], later employed kernel functions to solve high-dimensional image classification problems [13]. RotFor algorithm divides the training data into subsets (K) and applies principal component analysis to ensure diversity within each subset. Individual decision trees are constructed using the all components. Unknown class labels are determined through majority votes of the individual decision trees [14]. The CCF algorithm is an ensemble learning algorithm based on constructing multiple decision trees using canonical correlation analysis that maximizes the correlation between class labels and bands [15]. The U-Net architecture is a precise, end-to-end encoder-decoder network designed for semantic segmentation with a U-shaped structure [16]. It consists of two main components: the contracting path, which employs conventional convolutional neural network design to capture contextual information, and the symmetrical expansion pathway that achieves precise localization using transposed convolutions [17]. The contracting path encodes the image into a multi-level feature representation, and the symmetrical expansion pathway combines cropped feature maps with up-sampled ones, forming the U-shaped network structure.

Results

Segmentation parameters S, Sh and C were set to 34, 0.9 and 0.9, respectively. As a result, a total of 230,223 segments were created. To generate training and test datasets, 4,200 and 1,794 segments were collected on the orthomosaic. The hyperparameters for the ML algorithms were chosen as follows: C=500 and kernel type=rbf for SVM, K=8, and *nTrees*=300 for RotFor, and *nTrees*=100 for the CCF algorithm. .

To obtain a dataset for training of DL model, maize parcels in the orthomosaic were divide into 64x64 patch sizes. Data augmentation techniques were utilized to expand the training dataset artificially, such as rotating images 90, 180, and 270 degrees clockwise. A total of 9360 patches were collected, and the dataset was subsequently partitioned randomly into three segments: 80% for training, 10% for validation, and 10% for the test dataset. All image classification processes were carried out using a high-capacity workstation equipped with an NVIDIA GeForce RTX 3090 graphics card, an Intel® Core™ i9-12900K 3.2GHz 24-Core processor running at approximately 3.2GHz, and 128GB of RAM, which is accessible within the Advanced Remote Sensing Technology Laboratory (ARTLAB) of GTU Geomatics Engineering Department. The user-defined model hyper-parameters for the training phase were chosen as follows: a patch size of 64x64, 100 epochs, a batch size of 64, a learning rate of 0.001 for the Adam optimizer, and the utilization of the Categorical Cross-Entropy loss function. As an example of the produced crop maps, two maps generated using object-based RotFor and U-net models and the calculated overall accuracy (OA) and F-score (F-S) values are given in Figure 2.

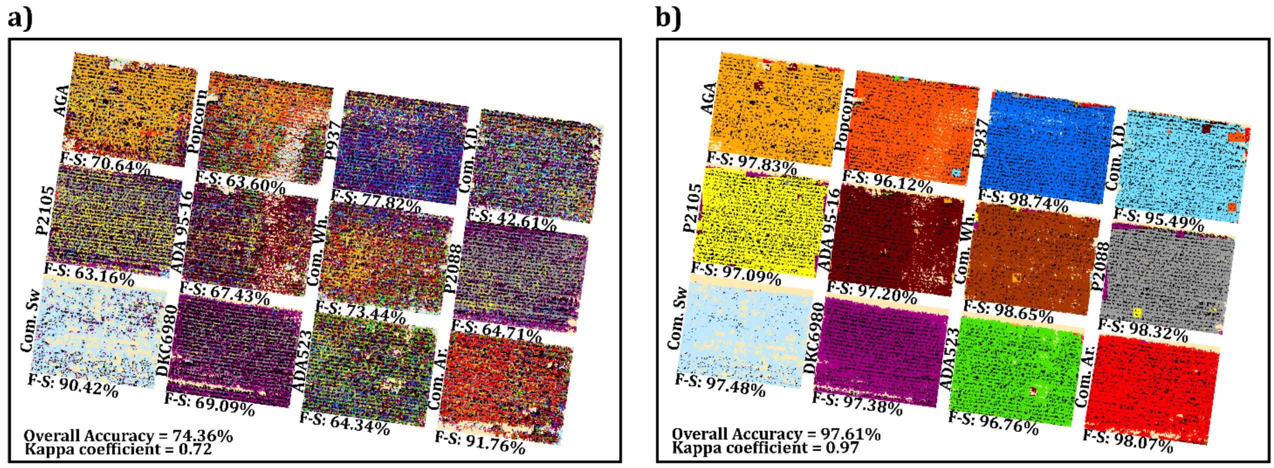

Figure 2. Crop maps produced by a) object-based RotFor and b) U-Net algorithm.

The OA values for crop maps produced through ML algorithms range from 72.30% to 74.36%. The RotFor algorithm demonstrated the highest accuracy among object-based classification methods, achieving a notable accuracy score of 74.36%. Additionally, comparable accuracy scores were noted in CCF (74.36%) and SVM (72.30%) algorithms. On the other hand, the U-Net model showed a superior performance in classifying different maize genotypes and the overall accuracy of the resulting crop map was 97.61%. When evaluating the class-based classification of maize crops, ML models achieved the highest and lowest F-score values for the Compozite Arifiye (Com. Ar.) and Compozite Yellow Dent (Com.Y.D) maize genotypes, respectively. In the RotFor algorithm, the F-score for Com. Ar. reached 91.76%, whereas it was 42.61% for Com.Y.D. Furthermore, the U-Net DL algorithm, which demonstrated significant superiority in overall accuracy, displayed class-based F-scores exceeding 95%. Compared to the object-based map produced by RotFor, the U-net generated crop map shows minimal confusion between classes.

Conclusion

This study aims to categorize 12 maize genotypes using ML and DL algorithms applied to MS UAV images. The quantitative assessments based on accuracy metrics reveal that the U-Net model excelled in classifying maize genotypes. While ML-based models achieved success rates above 90% for only two genotypes, the U-Net model achieved over 90% success across all genotypes. Despite the impressive performance of the U-Net model, the presence of distinctly delineated square shapes in patch-wise multi-class classification results indicates the necessity for further research on utilizing more robust DL-based models and high-resolution hyperspectral imagery.

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