Hassas Tarım Uygulamaları Üzerinde Makine Öğrenmesi Teknikleri Kullanımı

Usage of Machine Learning Algorithms on Precision Agriculture Applications

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***Özetçe*—Hassas Tarım, tarımsal üretimin devamlılığı, kalitesi, yeterliliği, karlılığı ve verimliliğini arttırmak adına verilen yönetimsel kararlarda tarımsal gözetim ve veri analizi teknikleri kullanılmasıdır. Bu teknolojiler, çiftçilere ürünleri, toprakları ve çevreleri hakkında uzaktan algılama sistemleri kullanıp kontrol ve bilgi olanağı sağlayarak karar verme süreçlerinde yardım etmeyi hedefler. Uzaktan algılama sistemleri bilgi toplamak için ışığın farklı dalga boylarını ayrı bantlarda filtreleyen multispektral kameralar kullanır. Spektral bantlardan elde edilen bitki örtüsü indeksleri, azot, klorofil ve su stresi gibi ürün özellikleri hakkında bilgi taşır ve bu bilgiler çiftçilerin, arazide herhangi bir ölçüme gerek kalmaksızın, sulama ve ilaçlama kararlarında yardımcı olacak niteliktedir. Bu çalışmada hassas tarım uygulamalarında makine öğrenmesi tekniklerinin kullanımının keşfi hedeflenmiş olup, Türkiye'nin Manisa ilçesindeki zeytin ağaçlarına yoğunlaşılmıştır. Bir İHA sistemine entegre edilmiş OCN kamerasının spektral verilerini kullanarak bitki örtüsü sağlık endeksi hesaplanmış ve veride bu endeksi baz alarak ağaç pikselleri diğerlerinden MinBatchKMeans algoritmasıyla ayrıştırılmıştır. Rekolte ve hastalık tahmini için en uygun öznitelikler doğruluk oranı karşılaştırmasına göre seçilmiştir. Rekolte verisi için Karar Ağacı Regresyon (KAR) modeli eğitilmiş, hastalık tahmini için Rastgele Orman Sınıflandırma (ROS) modeli eğitilmiştir. Ağaç piksel ayrıştırma sonucunun doğruluk oranı 0.85 ve 0.95 arasında belirlenmiş, KAR algoritmasının R2 puanı 0.99 ve ROS algoritmasının doğruluk oranı 0.98 olarak hesaplanmıştır, bu da bitki örtüsü indekslerinin önemi ve kullanışlılığını vurgulamaktadır.**

Anahtar Kelimeler—makine öğrenmesi, yapay zeka, hassas tarım, rekolte tahmini, hastalık tahmini, bitki ayrıştırma

***Abstract*—Agricultural monitoring and analysis of data to be used in management decisions to increase the quality, profitability, sufficiency, continuity and efficiency of agricultural production is called Precision Agriculture.[1] Precision Agriculture technologies aim to help the farmers with the decision making process by providing them information and control over their land, crop status and environment using remote sensing systems. Remote sensing systems use multispectral cameras to gather information, which filter different wavelengths of light in separate bands. Vegetation indices derived from the spectral bands of the remote sensing systems carry useful information about crop characteristics such as nitrogen content, chlorophyll content and water stress which supports the farmers to plan irrigation and pesticide spraying processes without the need of manual examination, providing a cost and time-efficient solution. This study aims to explore three specific Precision Agriculture applications, such as crop segmentation, illness detection and yield prediction on olive trees in Manisa, Turkey by using machine learning algorithms. Using the spectral band information gathered from an Orange-Cyan-NIR (OCN) camera embedded UAV system, vegetation health index was calculated and the data was preprocessed by segmentating the tree pixels from background based on those values using MiniBatchKMeans algorithm. Optimal features were selected based on accuracy comparison for yield and disease predictions. A Decision Tree Regressor (DTR) model was trained for yield prediction while a Random Forest Classifier (RFC) model was trained for disease prediction. The results showed that crop segmentation had an accuracy rate of 0.85-0.95, while DTR and RFC models had an R2 score of 0.99 and accuracy rate of 0.98 respectively, which displayed the importance and usefulness of vegetation indices.**

Keywords—machine learning, artificial intelligence, precision agriculture, yield prediction, disease prediction, crop segmentation

I. INTRODUCTION

Agriculture is one of the most important aspects of a developing civilization. However, managing the lands is not an easy task considering the increasing field sizes due to population growth, mechanization and intensive production.

The development of technology, especially sensing systems and cameras, brought opportunities which can be used to handle the problem. Remote sensing imagery, with features such as providing geographic information with centimeter accuracy and information heavy representation of a given area with the help of multiple spectral bands contained within in different resolutions, was proven to be helpful to give fast, accurate results over an area.

Agricultural monitoring and analysis of data to be used in management decisions to increase the productivity, quality, profitability, sufficiency and continuity of agricultural production is called precision agriculture, which uses the sensing systems to gather and interpret data. Machine learning, the ability to learn from past data to predict future behaviour, can be used in order to make sense of the data to make predictions over the land to determine irrigation and spraying areas, crop illnesses and amount of yield, which satisfies some of the aims of precision agriculture.

The paper explores the usage of machine learning methods over vegetation areas using a UAV system to segmentate crop areas, determine crop illnesses and predict yearly yield. Chapter II is separated into 3 sections and displays recent work on the usage of machine learning for each Precision Agriculture application stated above. Chapter III is focused on the materials and the methodology of the paper. Chapter IV presents the results of the proposed method and discusses ideas about how to improve the method further. Chapter V summarizes the paper and gives final thoughts about the subject.

II. LITERATURE REVIEW

This chapter covers the recent developments considering the applications of Precision Agriculture. The literature will be discussed in 3 sections.

A. Crop Segmentation

As real data is chaotic and images taken from a field contains both soil, vegetation and other elements that can affect the further processes, the first step is to separate the vegetation from the others. This section covers the recent works in this subject.

Bai et al suggested color segmentation in L*a*b* color space on images of rice plants. They proposed their own morphology modeling method on color distributions for different L slices. Their accuracy rate was 87.2% using ATRWG evaluation method and they claimed to get 96% accuracy rate using another evaluation method. [2] Torres-Sanchez, Lopez-Granados & Pena proposed an object based method for finding an optimal threshold to determine crop coverage using Object Based Image Analysis tool using vegetation indices and reported their method as a success. [3] Huang, Li & Chen proposed a model for tree crown detection from UAV images using watershed segmentation algorithm on bias field estimation of the image. They used F-score to evaluate their detection rate and got results of 98.2% and 93.1% for Osmanthus and Podocarpus trees respectively. [4] Lottes et al worked on sugar beets and proposed a segmentation algorithm on UAV images for crop and weed classification. They trained a Random Forest Classifier (RFC) model and evaluated their success rate by recall and precision evaluation metrics and their results showed a recall of 78% and precision of 90%. [5]

B. Yield Prediction

Estimation of yield before harvest helps the farmers to plan import/export decisions and tend to areas with low yield values by irrigation, crop rotation or spraying. This section explores the recent works based on the subject.

Pantazi et al worked on estimating yield of a wheat field and compared three neural network algorithms named Counter Propagation Artificial Neural Network (CP-ANN), XY-Fused Network (XY-Fs) and Supervised Kohonen Network (SKN) using satellite imagery. They used cross validation evaluation metric and their results showed that SKN had the best performance compared to the other algorithms with an overall accuracy of 81.65% while CP-ANN and XY-Fs had the overall performance of 78.3% and 80.92% respectively. [6] Ashapure et al proposed a 3-layered ANN model for yield estimation of tomato fields using UAV imagery and tested their model on 3 yearly acquired yield datasets. Their results showed R2 scores in between 0.78 and 0.89. [7] Panda et al proposed Back Propagation Neural Network algorithm on corn fields using vegetation indices comparatively and reported accuracy scores of 90%, 97% and 98% for 3 yearly yield datasets respectively. [8] You et al proposed a Convolutional Neural Network (CNN) and Long-short Term Memory Network (LSTM) model on soybean fields using a RGB multispectral camera. They evaluated their models using the Root Mean Squared Error (RMSE) metric and reported that their method outperformed the traditional remote sensing methods by 30%. [9]

C. Disease Prediction

Early detection of crop diseases is another important subject for the farmers to control the damage, plan pesticide spraying operations and separate diseased crops from the healthy to prevent spreading. This section covers the recent work based on the subject.

Ferentinos implemented multiple Convolutional Neural Network models to detect disease over several crop species. He trained AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat and VGG models. His results showed that the VGG model outperformed the other models with 99.53% accuracy rate. [10] Khamparia et al focused on several crops and diseases and proposed a Deep Convolutional Encoder Network for classification. Their results showed 97.5% accuracy rate using 2x2 convolution filter while 100% with 3x3 convolution filter and they stated that their model outperformed the traditional models. [11] Pantazi et al focused on the detection of a Microbotryum silybum and implemented SKN, CP-ANN, XY-F models. They evaluated models' performance and reported that CP-ANN and SKN models acquired up to 90% overall accuracy rate while XY-F model performed generally better with 95.16%. [12] Chung et al focused on foolish seedling disease on rice seedlings using morphological and color analysis. They implemented a SVM model and selected the optimal features using a genetic algorithm. They evaluated their model and reported that the classification was performed in 87.9% accuracy rate. [13]

III. MATERIALS AND METHODOLOGY

There are two ways to acquire information, either by UAV or satellite using specialized cameras. The image produced from those cameras are called multispectral imagery. The information provided by the band data of the imagery is used to segmentate the crops, detect illnesses and predict monthly yield by training a machine learning model that takes the information as input.

Satellite imagery covers a much larger area and contains more band information than UAV multispectral cameras yet it lacks the resolution that UAV imagery provides. Table I displays the comparison between two methods.

As there is a significant loss of resolution and delay of data acquisition for satellite imagery, it is not useful for tree based operations that require more sensitivity. Satellite imagery can describe general information about the land's health, nitrogen and water status, which, while useful in other contexts, does not provide meaningful information for the purposes of this paper.

The paper focuses on olive tree fields in several districts of Manisa, Turkey and the tree data was gathered using a multispectral camera over several plots of land in May, July, August and September of 2019 to increase the data count and give variability to the dataset by introducing trees in variable states. The training data was created using the band information gathered from the cameras to explore the importance of light's reflectance and vegetation indices derived from that information.

A. Data Gathering and Preprocessing

A flight plan was constructed which determines the boundaries of an area of interest and a multispectral camera and GPS embedded UAV was flown over that area, taking photos in 1.5 second intervals from a height of 120 meters above.

Methods / Topics	UAV Imagery	Satellite Imagery
Cost	Travelling + drone repairs	High resolution imagery
Area of interest	Local	Wide
Bands	Limited	High amount
Spatial Resolution	< 6 cm, Very high resolution	Sentinel 2A resolution = 10 meters, Landsat 8 resolution = 30 meters
Data acquirement	User defined	Acquisition occurs every 10-15 days
Weather/Cloud coverage	Doesn't get affected by cloud coverage, can't fly in rain.	Affected by cloud coverage, weather conditions decrease the quality of image.

Table I. UAV and Satellite Imagery Comparison

OCN camera was used for data gathering as it provides more accurate information.[14] After the images are acquired, the next step is to create a map in order to start processing the data. Since the images are geo-codded, thus each have their respective latitude and longitude values, it is possible to combine the images to create a spatial model of the area. This process is done by using a photogrammetry software specialized in drone mapping and the result is called orthomosaic image. Camera specifications, camera lens and sensor information, are used as parameters in the combination process.

Since the camera filters light, sun's reflectance over the area is an important factor that can affect the accuracy of the process. A device was used to gather reflectance information and the images were calibrated based on calculated values.

Accuracy of the mapping process is also determined by Ground Control Points. which are points on the ground with known coordinates in the spatial coordinate system, Knowing these points makes the orientation and alignment of the photographs possible, so the mapping process can work properly. As the drone used for the paper had an embedded GPS tool, photographs already had geographic coordinates and the control points were defined automatically.

The next step is to determine matching image pairs, which means a pair of overlapping images that show the same part of the area from different positions. Comparison of an area with multiple and insufficient overlapping images can be seen in Figure 1. While the area with multiple overlapping images is a lot clearer and more detailed, the other area is distorted and blurry which proves the importance of overlapping images in photogrammetry and mapping.

Figure 1. Comparison of an area with multiple (left) and insufficient overlapping images (right)

B. Dataset Creation

When the orthomosaic creation is completed, the program then starts generating the DSM and DTM files. DSM (Digital Surface Model) is the approximation and the generation of a height map of the surface of the area, considering both the terrain and the objects on the terrain. DTM (Digital Terrain Model) considers only the height of the terrain of the area. Difference of the two gives the DCM (Digital Canopy Model) or CHM (Canopy Height Model), which is the height of the objects only, This information is particularly useful to segmentate the trees from other elements and determine age information. Figure 2 displays the comparison of DSM and DTM.

The created files are big in size as they cover bigger areas while the target area is usually quite smaller. Processing the files without editing consumes too much memory due to the amount of pixels need to be handled. Thus, KML (Keyhole Markup Language) files were used in order to crop the target area. KML is a specialized XML file that contains important geographic information about an area. Figure 3 provides the visual representation of a KML file on Google Earth.

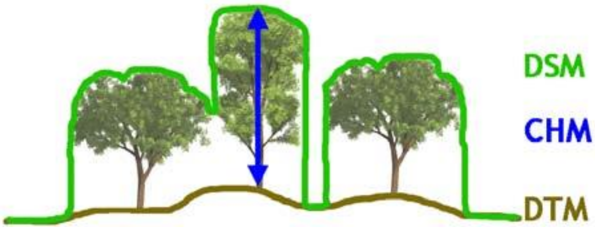

Figure 2. DSM and DTM comparison [15]

Figure 3. Visual representation of a KML file

Geospatial Data Abstraction Library (GDAL) is a software tool that is used for reading and writing raster geospatial data format. A raster image is a bitmap, which is a matrix of individual pixels that creates an image. Using this function of the library, band information of the images was extracted to create a dataset.

Each pixel in the image has its own 3 band information ranged between 0 and 255. However, multispectral bands are not enough for the segmentation process as they only relay the base reflectance information. Vegetation indices, equations which highlight a particular property of vegetation derived from different reflectance values, were also used in order to differentiate the pixels further. They often represent and can be grouped by 3 properties; health, nitrogen content and water stress. Some of the vegetation indices are given in Table II.

As the data in its raw form contains both vegetation and soil noise, pixels that belong to vegetation areas need to be isolated from the others. In order to do that, the pixels need to be classified and labeled based on their properties. Machine learning can be used to find patterns between the properties of pixels and classify each pixel according to the discovered relationship.

A clustering algorithm was more viable for the paper because of the lack of a training dataset. For the sake of saving memory and computation time, MiniBatchKMeans algorithm was used. While the method is faster than the traditional K-Means, there is a small decrease in quality.

Vegetation Index	**Usage**
Normalized Difference Vegetation Index [16]	Highlights vegetation's photosynthetic activity.
Soil Adjusted Vegetation Index [17]	Used on areas where vegetation cover is low and soil brightness is an influence.
Enhanced Vegetation Index [18]	Decreases soil noise and corrects atmospheric conditions. Used in areas with high concentration of vegetation.
Normalized Pigment Chlorophyll Ratio Index [19]	Determines chlorophyll content and nitrogen by looking at the difference between carotenoid and chlorophyll content of vegetation.
Nitrogen Nutrition Index [20]	Estimates nitrogen content of vegetation with optimization parameters based on land properties.
Normalized Difference Water Index [21]	Highlights water amount in water bodies such as lakes or seas
Normalized Difference Moisture Index [22]	Highlights variance of moisture in vegetated areas.

Table II. Vegetation Indices

Vegetation indices which chlorophyll content is highlighted were selected as parameters to segmentate the pixels as vegetation carries higher amount of chlorophyll compared to other elements in the image. The pixels that belong to clusters with higher cluster center values were selected as trees. The resulting image is called a canopy map. Figure 4 shows the segmentation result.

An additional clustering process was applied on the pixels that were identified as trees to determine outgrown weed areas. The reason for the additional process is that since weed is also vegetation, it can be falsely segmentated as a tree and affect the accuracy of the dataset negatively. The resulting image is called weed map and is given in Figure 5.

While each pixel has been classified into their respective groups and pixels that belong to vegetation were selected, each pixel is treated as they belong to the same tree. Precision agriculture principles require each tree to be individualized as the information comes tree-based and necessary operations are applied to trees individually. In order to achieve this, each pixel is turned into objects.

Traditional image processing techniques and contour detection can be used to turn the pixels into objects based on their boundary points. However, while traditional methods work well for non-overlapping pixels, they perform worse for the other case. Tree pixels often overlap and are falsely determined as the same object since the edge pixels are connected. Watershed algorithm can be used as an alternative to the traditional methods in order to correctly objectify the overlapping data, which uses Euclidean Distance Transform to determine the central point of each object and classify each pixel based on connectivity. Individualization result, with each tree marked and counted, is given in Figure 6.

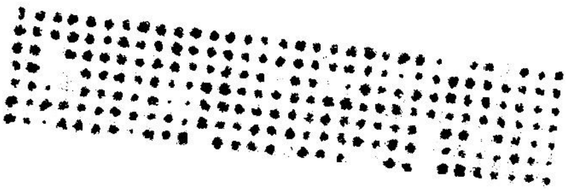

Figure 4. Canopy Map conversion

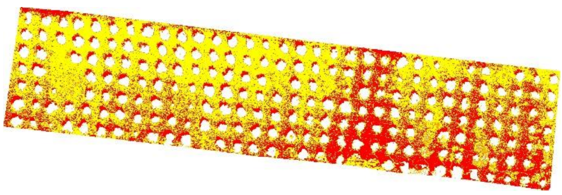

Figure 5. Weed Map

Figure 6. Individualization result

Chlorophyll content, nitrogen content and water stress maps of the tree pixels were created to further characterize each individual tree. While chlorophyll and nitrogen content maps show the general health of the trees and nitrogen amount contained within respectively, water stress map shows whether the irrigation is sufficient for the trees or not. Figure 7 shows each respective map.

C. Yield Prediction

Yield prediction is one of the most important applications of Precision Agriculture which helps the farmers to determine the low-yield areas to tend to and to make timely import and export decisions.

Evaluating all trees in an area is not optimal as it is time and resource consuming. For that purpose, several groups of trees which have low and high chlorophyll content were selected and those trees' monthly yields were evaluated on site. The reason why those specific groups were selected is to get an accurate overall yield for the area as selecting high or low values only can lead to a wrong calculation.

The estimated yield results were added to the training dataset with the trees' base reflectance and vegetation index information. A Decision Tree Regressor model was implemented as the model fit the dataset well.

Figure 7. Chlorophyll,Nitrogen and Water Stress Maps

Dataset was split 80%/20% into training and validation datasets in order to train the model and test for accuracy assessment. Optimal features were selected by considering the highest decrease in error function. The evaluation metrics were chosen as Mean Absolute Error, Mean Squared Error and R-squared (R2) score to determine the success of the model. The results show that Decision Tree Regressor model was a good choice for this dataset and the yield amount for trees can be successfully predicted using reflectance information, average tree pixel sizes and vegetation indices with an MSE of 0.02, MAE of 0.07 and R2 score of 0.99.

D. Disease Prediction

Another important application of Precision Agriculture is disease prediction as most of the diseases spread quickly and decrease the quality of the harvest considerably. Early detection of diseased areas also help with the amount of spraying and decision of medicine as each disease requires different procedures.

The data gathering process works similarly with yield prediction. Areas that have low chlorophyll content were selected and those trees were examined on site for diseases. The paper focuses on Palpita unionalis, which is a type of larva that feeds on fresh olive tree leaves and products, causing the yield to decrease considerably for the following years if it is not treated. [23]

A Random Forest classifier model was trained to predict diseased areas by feeding the model with both healthy and diseased area information. Dataset was split 80%/20% into training and test datasets. 204 instances were used for the training dataset while 51 instances were used for testing. Optimal features were selected based on the increase of accuracy score and confusion matrix was used to describe the performance. Confusion matrix after prediction process is given in Table III.

Experiments prove that Random Forest classifier algorithm works well for the features provided with an accuracy score of 0.98, precision of 1, recall of 0.97 and F1 score of 0.98 respectively.

IV. DISCUSSION

The results show that machine learning algorithms can be useful to predict future behaviour for Precision Agriculture problems and produce an estimation for yield and disease information of trees that would require manpower and resources to manually examine. Vegetation indices carry vital information and are useful for characterization of the trees.

Predicted / Actual	Palpita unionalis	Healthy
Palpita unionalis	32	1
Healthy	0	18

Table III. Illness result confusion matrix

While the discussed models work very well with the datasets provided, it is assumed that the weather conditions stay the same in all instances. Since weather conditions affect the light reflectance values, the vegetation indices also change. Thus, the assumption may lead to inaccurate predictions later on. It is helpful to gather data from the target area in several weather conditions to teach the model the behaviour of the light during different states for the predictions to be a lot more reliable by adding those different states as a categorical feature to the dataset.

Another way to improve the reliability of the model is more physical information such as soil type and nutrients. Even chemical information that might be affecting the soil or the crops at that moment since farmers tend to spray the area from time to time. Adding these information will improve the characteristics of the observed instances.

Weed grown in the area due to neglection affect the dataset if they were not handled beforehand. As their vegetation index values are similar to the tree data, it is difficult to separate them by clustering algorithms or manual thresholding. Thus, occurance of weed is considered noise and an effective noise removal algorithm is needed to handle the problem.

To sum up, while the base model acts sufficiently, there is still room to improve the model further by considering the issues stated in this section. Real data is chaotic and machine learning is rule based, thus it is important to prepare the model for each possible combination of events that can simulate real data.

V. CONCLUSION

The paper’s aim was to explore the usage of machine learning on Precision Agriculture applications. The primary focus was on three subjects, namely crop segmentation, illness detection and yield prediction.

Crop segmentation process was achieved using MiniBatchKMeans algorithm. The success rate of the model was observed between 85%-95%, worsening for areas that contain a lot of noise. For disease detection, the paper focused on Palpita unionalis, a type of tree worm that feeds on lively olive tree leaves and fruits. Random Forest classifier algorithm was used to determine the trees that contain the tree worms. The model was successful with an accuracy score of 98%. Lastly, for yield prediction, Decision Tree Regression algorithm was used which had a Mean Absolute Error of 0.02, Mean Squared Error of 0.07 and R2 score of 0.99.

With future work discussed in Chapter IV, it is highly possible to obtain a generalized model that has high predictive capabilities for agricultural data.

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