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SUPERVISED LEARNING FOR CROP /WEED CLASSIFICATION BASED ON COLOR AND TEXTURE FEATURES

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ABSTRACT

Precision agriculture has recently seen a surge in interest in computer vision techniques. All computer vision-based precision agriculture tasks have the objective of identifying and differentiating objects of interest (such as crops and weeds) from the backdrop. Unwanted plants known as weeds grow amid crops and compete with them for sunshine, water, and nutrients, lowering crop yields. Identification of weeds mapping is essential for site-specific weed control in order to lower labor costs and herbicide impact. This study examines the use of texture and color characteristics to distinguish between weeds and soybean crops. The Support Vector Machine (SVM) classifier is trained using feature extraction techniques such as the two color spaces (RGB, HSV), the gray level Co-occurrence matrix (GLCM), and the Local Binary Pattern (LBP). A publicly available image dataset of soybean crops from an unmanned aerial vehicle (UAV) was used for the experiment. According to the experiment's findings, the combination of color and LBP traits produced the best accuracy (over 96%). The following index terms are used: color characteristics, local binary pattern (LBP), gray level co-occurrence matrix (GLCM), crop/weed categorization, and support vector machine (SVM).

Keywords: Weed identification, Precision Agriculture, Support Vector Machine, Color Characteristics, Local Binary Pattern

INTRODUCTION

Precision agriculture (PA) has seen a lot of effort in recent years, especially in the monitoring area. Precision agriculture uses information from several sources to increase agricultural yields and the economic efficiency of crop management techniques, such as irrigation and fertilizer inputs. Administration and the use of pesticides. A farmer can use PA to apply the appropriate amount of treatment at the appropriate time and location. Due to their ability to capture high spatial and temporal resolution photographs of the entire agricultural field, unmanned aerial vehicles (UAVs) can now be used in a wide range of crop management applications. Satellite acquisitions, since they make it possible to quickly and affordably acquire the field with extremely high spatial resolution.

LITERATURE SURVEY

Agricultural Remote Sensing," M.A. Fried One of the most significant and extensively used applications of remote sensing is the mapping and monitoring of croplands. Indeed, the demand for better agricultural monitoring at the local, regional, and global levels led to the development of a large portion of the methodological and technological foundation for modern land remote sensing. The initial proof-of-concept and methodological basis were established by early field experiments such as LACIE and Ag RISTARS, which showed that remote sensing could map a wide range of cropland attributes, such as crop type, crop health, crop phenology, and soil and canopy attributes. The depth, breadth, and sophistication of remote-sensing applications in scientific research and farmland management have quickly increased over the past few decades due to advancements in technology, processing capacity, and analysis techniques. An overview of remote sensing in croplands.

"A review of the use of small unmanned aerial systems in precision agriculture," precision farming. J. M. Kovacs and C. Zhang. The use of geospatial methods and sensors (such as GPS, remote sensing, and geographic information systems) to detect changes in the field and address them with different approaches is known as precision agriculture (PA). In particular, it is now more usual to analyse these fluctuations for soil and agricultural conditions using high-resolution satellite photography. The availability of such imagery and its frequently exorbitant costs, however, would point to the need for an alternate product for this specific PA use. Given their cheap operating costs in environmental monitoring, photographs captured by small unmanned aerial systems (UAS), also known as low altitude remote sensing platforms, are specifically highlighted.

A Comprehensive Analysis of UAV-Based Precision Agriculture Applications," Information P. G. Sarigiannidis, S. Bibi, and D. C. Tsouros The collecting of real-time environmental data is made possible by emerging technologies like the Internet of Things (IoT), which have great potential for use in applications related to precision agriculture and smart farming. Due to their ability to capture photos with high spatial and temporal resolution, Internet of Things devices like Unmanned Aerial Vehicles (UAVs) can be used in a number of crop management applications. Agriculture is predicted to undergo a revolution thanks to these technologies, which will allow decisions to be made in days rather than weeks and promise a considerable decrease in costs and an increase in productivity. As a result, the four pillars of precision agriculture—applying the correct practice, at the right place, at the right time, and with the right quantity—are supported. In this piece, we examine the latest uses of UAVs in precision farming. Additionally, we highlight the most widely used techniques for processing aerial imagery, go over the results of each technique, and talk about how each might be used in farming operations. the kinds of UAVs that are exploited, after which we concentrate on the technology and data collection techniques, identifying the advantages and disadvantages of each.

"Detection of Weeds in UAV Images with SLIC and Hough Transform," The Seventh International Conference on Image Processing Theory, Tools, and Applications (IPTA) Proceedings & Proceedings, Montreal. M. D. Bah, A. Hafiane, R. Canals Herbicides were typically sprayed in all fields to control weeds. This approach affects both the environment and human health in addition to requiring massive amounts of herbicides. In this work, we provide a novel approach to using images from an unmanned aerial vehicle (UAV) to distinguish between crops and weeds. The Hough transform, the vegetation skeleton, and the spatial relationships of superpixels produced by simple linear iterative clustering (SLIC) form the foundation of this technique. Intraline weed detection is made possible by the spatial link of superpixels and their locations within the identified crop lines. Our approach demonstrates its resilience when there are weed patches along crop lines and when crop lines are detected in addition to weeds.

Discriminating crops/weeds in an upland rice field from UAV images with the SLIC-RF algorithm," PLANT PRODUCTION SCIENCE, Taylor and Francis 2020 K. Kawamura, H. Asai, T. Yasuda, P. Soisouvanhc and S. Phongchanmixay, In this study, we propose a method for discriminating crops/weeds in upland rice fields using a commercial unmanned aerial vehicles (UAVs) and red-green-blue (RGB) cameras with the simple linear iterative clustering (SLIC) algorithm and random forest (RF) classifier. In the SLIC-RF algorithm, we evaluated different combinations of input features: three color spaces (RGB, hue-saturation-brightness [HSV], CIE-L*a*b), canopy height model (CHM), spatial texture (Texture) and four vegetation indices (VIs) (excess green [ExG], excess red [ExR], green-red vegetation index [GRVI] and color index of vegetation extraction [CIVE]). Among the color spaces, the HSV-based SLIC-RF model showed the best performance with the highest out-of-bag (OOB) accuracy (0.904). The classification accuracy was improved by the combination of HSV with CHM, Texture, ExG, or CIVE. The highest OOB accuracy (0.915) was obtained from the HSV+Texture combination. The greatest errors from the confusion matrix occurred in the classification between crops and weeds, while soil could be classified with a very high accuracy. These results suggest that with the SLIC-RF algorithm developed in this study, rice and weeds can be discriminated by consumer-grade UAV images with acceptable accuracy to meet the needs of site-specific weed management (SSWM) even in the early growth stages of small rice plants.

An Automatic Random Forest-OBIA Algorithm for Early Weed Mapping between and within Crop Rows Using UAV Imagery". Remote Sensing De Castro, Ana I and Torres-Sanchez, Jorge and Pe ´ na, Jose M and ˜ Jimenez-Brenes, Francisco M and Csillik, Ovidiu and L ´ opez-Granados, ´ Francisca Accurate and timely detection of weeds between and within crop rows in the early growth stage is considered one of the main challenges in site-specific weed management (SSWM). In this context, a robust and innovative automatic object-based image analysis (OBIA) algorithm was developed on Unmanned Aerial Vehicle (UAV) images to design early post-emergence prescription maps. This novel algorithm makes the major contribution. The OBIA algorithm combined Digital Surface Models (DSMs), orthomosaics and machine learning techniques (Random Forest, RF). OBIA-based plant heights were accurately estimated and used as a feature in the automatic sample selection.

EXISTING SYSTEM

The The current approach to classifying crops or weeds and suggesting crops involves human error, manual labor, and yields unpredictable results. In addition, the process is time-consuming and intrusive. A camera or other imaging device is used to take pictures of weeds and crops. Before being converted to an appropriate color space (such as RGB, HSV, or LAB), images are scaled and normalized.

IMAGE ACQUISITON: It is characterized as the act of taking pictures. We believe that webcam-based pre-processing techniques are the most effective. These pictures are being called using Matlab syntax functions.

Pre-Processing: It is used to alter images, eliminate undesirable noise, and prepare for the future. 1.Image Compression,

2.Image Enhancement

3.Envinronment Conditions

HSV BASED METHOD

Hsv color space:

The hue (H) orefers to the pure color that a color is most like to. The hue of all red tints, tones, and shades is the same. As a fraction between 0 and 1, hues are denoted by a number that indicates where the matching pure color is located on the color wheel. The color wheel has values of 0 for red, 1/6 for yellow, 1/3 for green, and so on.

The saturation (S) characterizes the degree of whiteness of a hue. has a saturation of 1; white

$$H = \left[\frac{H}{255} * 360\right] |360|$$

$$S = \frac{S}{255}$$

$$V = \frac{V}{255}$$

has a saturation of 0; while red tints have saturations below 1.

HSV Based Histogram The segmented pictures' Hue, Saturation, and Value (HSV) histogram is determined. Hue, Saturation, and Value (HSV) color space is quantized from the input image using 8 x 2 x 2 identical bins. Histogram output is a 1 x 32 vector that includes the photos' hue, saturation, and value. The distribution of different bright and dark tones inside an image is described by an image histogram, a sort of histogram that serves as a graphic depiction of tonal distribution. Redistributing tones can lighten a dark image or darken a bright image during the scanning or image editing process. The number of pixels for every tonal value is represented in this histogram. One can assess the full tone distribution of an image by examining its histogram. A lot of contemporary digital cameras provide image histograms. Tonal variations are shown on the graph's horizontal axis, while the number of pixels in a given tone is shown on the vertical axis.

The value (V) of a color, also called its the color's brightness indicates how dark it is. Black is equal to 0; brightness increases as one moves away from black. Given that RGB values typically fall between 0 and 255, we must apply the following formulas to convert the hue values between 0° and 360°, the saturation values between 0 and 1, and the values between 0 and 1. The image is separated into distinct sections based on hue and saturation values following the conversion of the full image from RGB to HSV color space.

DRAW BACKS:

1.Is unable to classify rock, crop or weed masses.

2.Requirements for Large Training Data: work best when trained on a sizable and representative dataset. For crop or weed texture classification, gathering and labeling an extensive dataset can be costly and time-consuming.

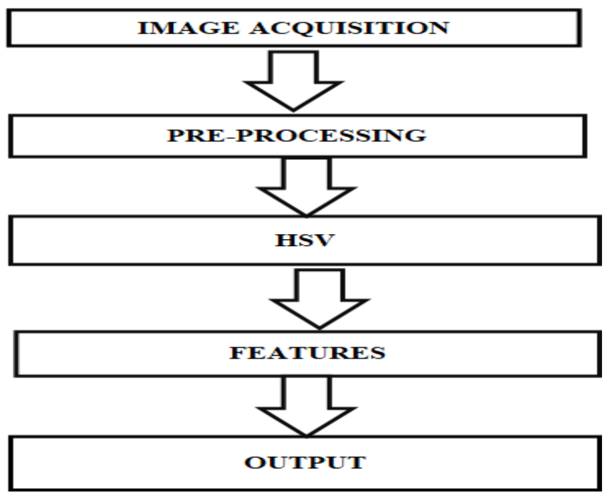

Fig 1: Representation of tonal distribution describes the distribution of various bright and dark tones with in an image.

PROPOSED SYSTEM

Precision agriculture (PA) has been quite active in recent years, especially in the monitoring area. In order to increase agricultural yields and the cost-effectiveness of crop management, precision agriculture uses data from several sources. Techniques such as the use of pesticides, irrigation control, and fertilizer inputs The difficulty in classifying crops and weeds figuring out HSV. To extract features, GLCM and Gabor Wavelet algorithms are employed feature extraction based on color, or HSV. For texture-based feature extraction, gabor filters are employed. Next, the characteristics derived from the test image and the features derived from the dataset's photos are contrasted. Statistical measures such as mean, standard deviation, skew, and kurtosis are used to train the Decision Tree classifier in order to match picture features. Lastly, the expected crop or weed The current approach to classifying crops or weeds and suggesting crops involves human error, manual labor, and yields unpredictable results. The procedure takes a lot of time and is intrusive. However, our suggested system gets beyond all of these mistakes since it considers the physical characteristics of the crop or weed.

Feature Extraction:

The basic elements of an object are its features. It is employed in order to differentiate one object from another. Descriptors can also be Description of an object is the process of extracting its features. There are two ways to extract features in our suggested system.

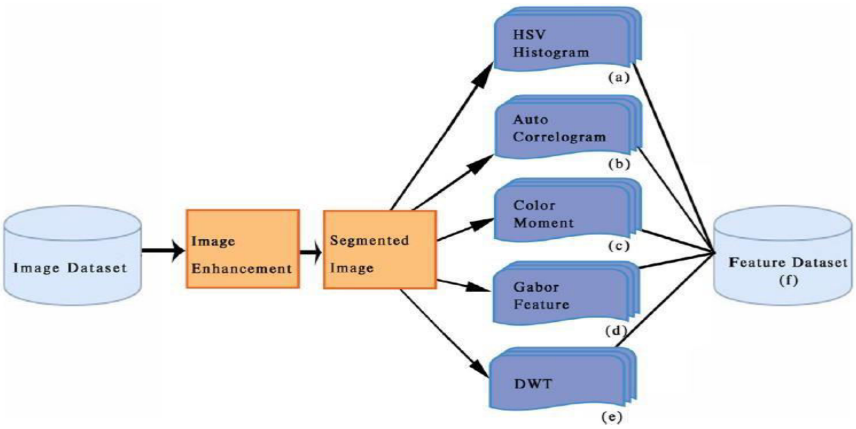

Fig 2: Proposed System for Fruit Detection

Colour moments: Present a grayscale image of every color channel. Observe that the figure has a white area in each of the divided color planes. The purest tones of each distinct color are represented by the white.

Colour correlation: The auto correlogram for color is computed. It is employed in order to determine the spatial correlation between identical pixels. In RGB color space, which is 4 x 4 x 4, the input image is quantized into 64 colors in order to implement color auto correlogram. A 1x64 feature vector with a color auto correlogram is the output's format. This approach uses a distance set d = {1 3 5 7} and employs dynamic programming, as recommended. Since the precision of the 3D reconstruction is dependent on the accuracy of the matching, matching is a crucial problem in computer vision.

Data Set

There are five distinct classes within the data set. A single crop and weed type is represented by each class. The classes that have been selected include weed, ground nuts, maize, and rice.

Gabor feature of photos of weeds or crops is computed. The Gabor feature of an input image can be found using the Gabor wavelet approach. This technique is employed to determine the

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mean-squared energy.

Discrete wavelet transform: The discrete 2-D wavelet decomposition at a single level is carried out. The input image's wavelet coefficients are taken out. The discrete wavelet transform's mean and standard coefficients are contained in the feature vector. There are other books and papers on the subject that cover the discrete wavelet transform and theory of multi-resolution analysis, however this is outside the purview of this tutorial.

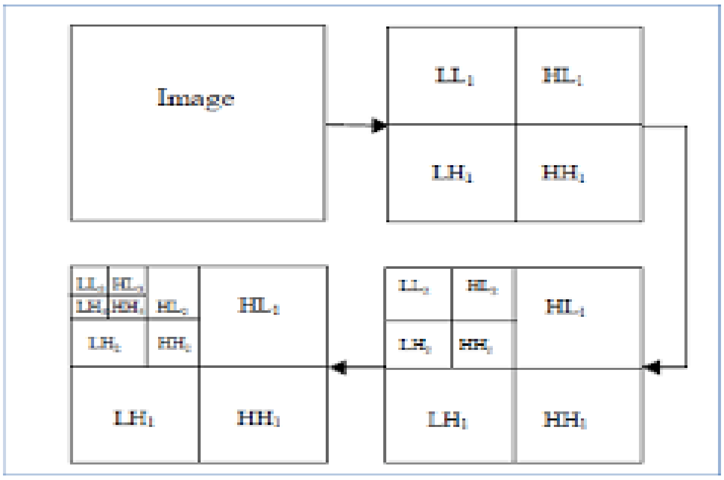

Fig 3: Construction of 2-D Discrete wavelet

2-D Discrete wavelet construction: The definition of DWT of image f (x, y) is as follows: where A and D coefficients represent roughly and differently directional components, respectively. These can also be referred to as the picture's low frequency and high frequency subbands.

$$f(x,y) = A_n^q f(x,y) + \sum_{s=1}^{n} \left[D_{s,1}^q f(x,y) + D_{s,2}^q f(x,y) + D_{s,3}^q f(x,y) \right]$$

The low frequency portion of the image and n clusters of high frequency. The 2-D real wavelet is used to generate the analytic extension. We can acquire a low frequency component and n sets of high frequency components once the image has been decomposed by DWT. In Figure 1, the image's DWT decomposition structure is displayed. Bands 1 through 4 are the four low frequency subbands that make up the low frequency portion, which is represented by the term "low." Three directions—horizontal (H), vertical (V), and diagonal (D)—are used to display the high frequency data at each level. Each direction has four subbands: band 1, band 2, band 3, and band 4. It is possible to convert these four subbands into three phases and one magnitude. The discrete wavelet transform's output size for the mean and standard coefficient feature.

Classification: Classification is the process of categorizing; to classify, we use a classification method. distinct kinds of fruit. SVM is useful. The original data would be reduced to a representation that captures as much of the original variance as feasible if we drew a line perpendicular to the regression line from each point and used the intersection of

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those lines as an approximation of the original data point. In Figure 2, you can see that a second regression line is displayed perpendicular to the first.

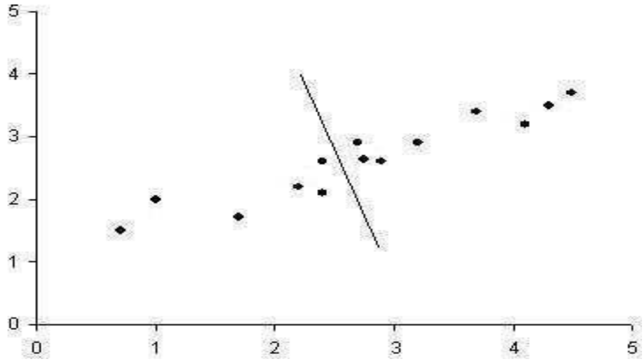

Fig 4: Regression line along second dimension captures less variation in original data

Accuracy for multi SVM

SVM with a kernel function is used to classify the crop or weed. A kernel, which is a similarity function, determines the degree of similarity between two inputs. In this work, the crop or weed classes are classified using SVM with a linear kernel. The rationale of employing a linear kernel is explained One of the simplest and fastest kernel approaches for SVM is the linear kernel. When there are too many features in the images, the linear kernel performs well. This is due to the fact that moving the data to a higher dimensional space does not actually enhance the classifier's performance. This extracts seven distinct characteristics from the crop or weed image and provides varying feature values for a single image. It is discovered that one image, measuring 1x193, has a significant feature size. Therefore, to categorize the crop or weed classes, the linear kernel with SVM is used. We gathered and assembled visual data of different types of weeds and crops.

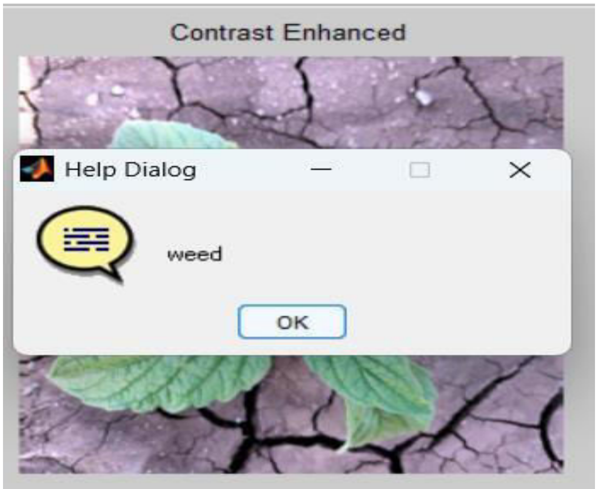

Fig 5: Weed

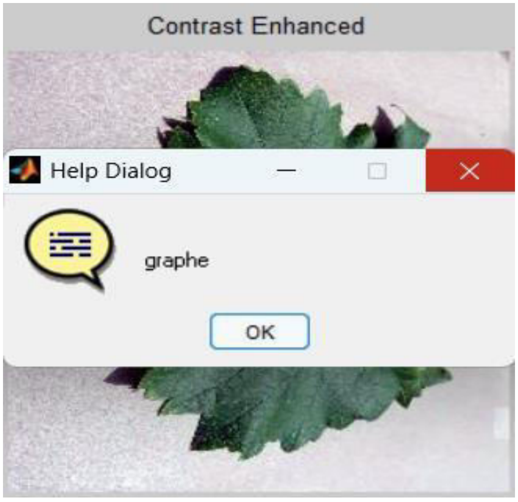

Fig 6: Graphe

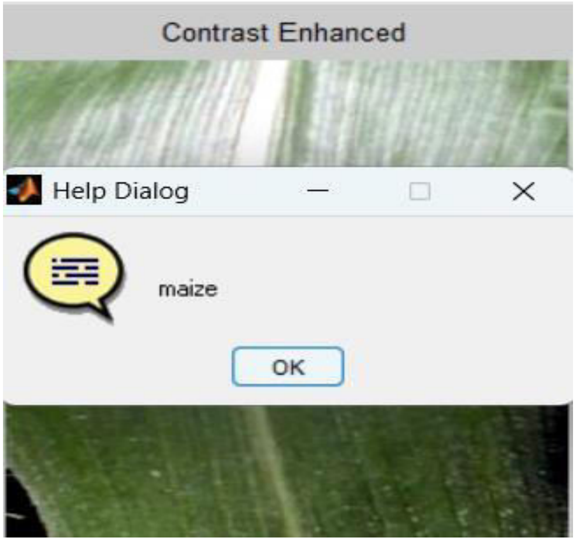

Fig 7: Maize

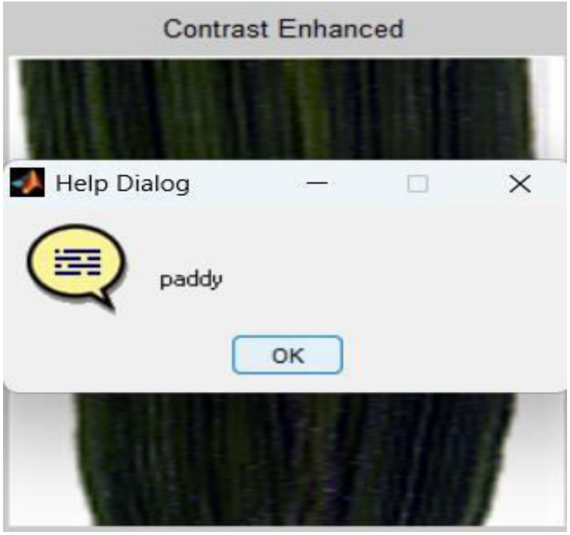

Fig 8: Paddy

CONCLUSION

In this study, we used SVM classifiers on UAV photos to distinguish between weeds and crops. The input features listed below have been assessed: color extractor, textual characteristics, and color attributes. The confusion matrices for various combinations have been acquired. The addition of texture information to color space improved the misclassifications, which we found mostly happened between the crop and weed classes. Because green vegetation has a substantial color contrast between crops and weeds, it is possible to distinguish between the two with accuracy using simply color features. Color characteristics and the extractor result in more reliable classification accuracy results. Excellent results were obtained with a one-versus-one strategy using the SVM classifier, which is computationally efficient and has an accuracy of over 96% in classifying all classes.

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