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TOBACCO PLANT REGION EXTRACTION AND SEGMENTATION USING WATERSHEDAND CNN ALGORITHM

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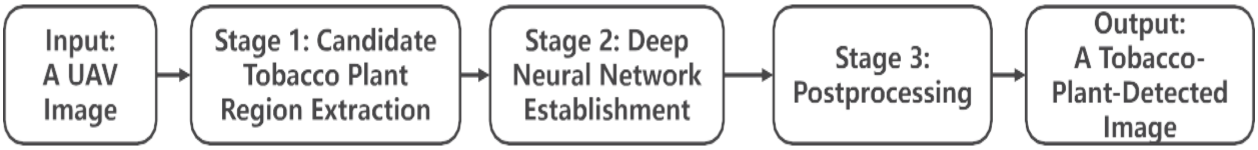
ABSTRACT:
The importance of plants cannot be overstated since they play critical roles in sustaining life on earth while also providing numerous benefits to human beings. Understanding different plant species is crucial not only from a research standpoint but also from an environmental perspective as well as preserving biodiversity; however traditional methods based on keys are cumbersome and frustrating because it uses technical botanical terminology making it difficult even for experts in some cases let alone novices. Fortunately, today's ubiquitous digital technologies like high resolution mobile cameras and enhanced remote access to databases offer solutions to this problem. With the assistance of advanced image processing techniques and pattern recognition algorithms like neural networks automated plant identification is now a reality. The realm of machine learning dominates computer science research presently and its scope is broadening daily. Among the multiple fields within this domain convolutional neural networks stand out as particularly popular and well suited for tasks such as image classification - like the one employed in this project.

1.INTRODUCTION:
Whenever we gaze upon an image that presents to us an object or person's appearance (think: photographs or paintings), it allows for a visual interpretation by creating amplitude distributions of colors via picture processing; screens, holograms -- anything two-dimensional really -- fall under this category too! Present-day technology has grown so much that computer graphics can make faux photography nearly indistinguishable from real ones! From maps to pie charts; if you perceive it on a flat surface with lines and shapes in colors-it falls under the "image" category. We need not limit ourselves to traditional means like drawing/painting but explore advanced machinery- printers included -to produce breath-taking imagery! However transient they may be labeled if they don't stand still for long. Reflections on mirrors, projections from camera obscuras and CRT displays represent some methods used to capture or display images today whereas fixed images describe photographs saved digitally or on physical mediums like paper/cloth. Digital Image Processing refers to the use of computer algorithms when working with these forms of photos which provides significant improvements over analog options since it is part of digital signal processing. A vast array of algorithms exists for handling input data, resulting in many possible methods for data manipulation. Processing pictures without encountering issues like noise build-up or signal distortion is essential for obtaining accurate results. With their multiple dimensions, pictures lend themselves well to analysis via UAVs at low altitudes- the result being high-quality spatial resolution imagery on the order of just centimeters! Identifying specific objects or object classes plays a pivotal role across many industries; witness Fergus et al.'s algorithm which recognizes patterns even when given no labelling information as well as Agarwal et al.'s work which produces automated detection of object types within new pictures- both techniques offer exciting developments moving forward! One class of particular interest from this research is tobacco plants which hold great significance across an array of contexts. The significance of the tobacco plant in driving the economies of China, India, Brazil and the United States cannot be overlooked.
As an alternative solution our team has implemented deep neural networks to identify tobacco plants from aerial images captured by UAVs for a more efficient approach. Deep neural networks have become increasingly popular since 2006 with new algorithms introduced that enhance their learning capabilities - making them ideal tools for image analysis and interpretation applications such

as ours! One early type of these powerful machines is convolutional neural networks (CNNs) first proposed back in the 1970s. When it comes to inspiring ideas for advanced technology like computer vision systems imitating nature is often a great starting point. Convolutional Neural Networks (CNNs) were created by studying how animal brains work: specifically, the visual cortex [26]. Though initially developed to recognize handwritten characters which was quite challenging at that time. Incredible enhancements have been made thanks to rapid developments in deep neural networks; including advancements in both framework design and training algorithms. Today's CNN systems offer an array of solutions when it comes to dealing with vision tasks - even those involving remote sensing images.

This research aims to contribute new solutions for analyzing tobacco planting in UAV images through the development of an automatic detection algorithm. Specifically, our focus is on detecting and counting individual plants using a three-stage process: candidate region extraction, classification with deep learning techniques (CNN), followed by further refinement through postprocessing techniques. The proposed framework enhances current knowledge on this topic while also offering practical applications beyond just tobacco farming analysis.



Here we are excited to present our ground breaking findings - marking the very first time that UAV imagery has been employed for detecting instances of tobacco plant growth. Through developing a proprietary algorithm specifically tailored for this task and subjecting it to rigorous assessment using a significant number of UAV images we are confident in our conclusions. Our research project began by examining high resolution images captured via drones over agricultural land which housed significant areas densely populated with flue cured tobacco.

This approach allowed us to utilize the incredibly precise spatial details provided by drone footage in order to detect even individual instances of plant growth effectively. Our algorithm is structured into three separate stages - commencing with isolating a series of candidate regions within each image that showed indications suggestive of containing recognizable tobacco plant life. Carefully selecting different locations within an image is crucial when analyzing.

2.PROPOSED METHODOLOGY

Let us consider a high-resolution image I (x, y) (where (x, y) represents pox ell coordinates in image) captured by a UAV overran agricultural region of tobacco planting. UAVs can obtain images with high spatial resolutions when they fly at relatively low altitudes (several hundred meters). The high level of detail in UAV images provides much postprocessing is performed to further remove the nontobacco plant regions. The framework of the proposed algorithm is shown in Fig. 1. The image notations and their definitions used in the proposed algorithm are shown in Table I.

Our algorithm is structured into three separate stages - commencing with isolating a series of candidate regions within each image that showed indications suggestive of containing recognizable tobacco plant life. Carefully selecting different locations within an image is crucial when analyzing them for containing either tobacco or nontobacco vegetation in each area under review. Therefore, we deploy a CNN model optimized for recognizing such features effectively based on their characteristics specific to this task's requirements; it classifies different locations confidently with minimal errors into two categories: those containing healthy crops versus those with toxic ones ready for eradication using specialized herbicides formulated exclusively by us at great expense but worth every penny spent because they protect against dangerous environmental hazards caused due partly due human activity worldwide causing air pollution levels high enough so that even airplanes do not fly above some areas!

To achieve our research goals, we have developed a three-stage algorithmic approach aimed at detecting and counting plants visible in UAVs. The first stage of this process involves selecting multiple potential candidate tobacco plant regions while avoiding the non-tobacco ones present in the UAV images.

In order to identify locations with potential tobacco plants present in UAV images we have developed a three-stage algorithm. Our first step involves extracting all image regions containing either a tobacco plant or other vegetation.

We then employ a CNN model to classify these candidate regions as either containing a tobacco plant or not. Finally post processing techniques are used to refine the results and remove any non-tobacco areas. Figure 1 provides an overview of our proposed methodology while Table I defines important notation terms used throughout our algorithm. Extracting potential tobacco plant regions accurately requires attention paid to four key steps.

1) noise filtering;
2) soil region detection;
3) plant region segmentation; and

4) plant region extraction

Figure 3 illustrates how we extract candidate tobacco plant regions from UAV images without interference from soil patches. 1.NOISE FILTERING: Using a Gaussian kernel with optimized values, we first filter out any unwanted noise present in our data before applying an extra-green method for precise identification of soil areas. By leveraging these techniques, our approach identifies key features required to isolate target locations accurately within complex imagery data sets. $(x, y) = I\ (x, y) * w\ (x, y)$ where I_d is the denoised UAV image. $w\ (x, y)$ is of dimensions m = 3 3, mean μ = 0, and variance σ^2 = 0.25.* Represents the convolution operation.

2. Soil Region Detection: UAV images generally contain soil regions. In order to reducethe influence of soil regions, the extra-greenmethod is applied to remove the soil regions andpreserve the plant regions in UAV images, which is defined as follows:

$B_{pr} (X, Y) = B_{gr} (X, Y) \cap B_{gb} (X, Y) B_{gr} (X, V) = 1 \ I_{gr} (X, Y) > w1$

$B_{gb} (X, V) = 1 \ I_{gb} (X, Y) > w2$

$I_{gr} (x, y) = I_g (x, y) - I_r (x, y)$

$I_{gb} (x, y) = I_g (x, y) - I_b (x, y)$

where B_{pr} is the resultant binary image containing the plant regions. I_g, I_r, and I_b are the green channel, red channel, and blue channel of image I_d. I_{gr} is the difference image between $I_g$and I_r, and I_{gb} is the difference image between I_g and I_b. B_{gr} isthe binary image obtained by thresholding the difference image I_{gr}, and B_{gb} is the binary image obtained by thresholding the difference image I_{gb}. ω_1 and ω_2 are depth control parameters. In our experiment, ω_1 and ω_2 are set as 0.05 and 0, which were selected according to the RGB values of lawn green (R = 0.486, G = 0.988, B = 0) and spring green (R = 0.235, G = 0.702, B = 0.443).

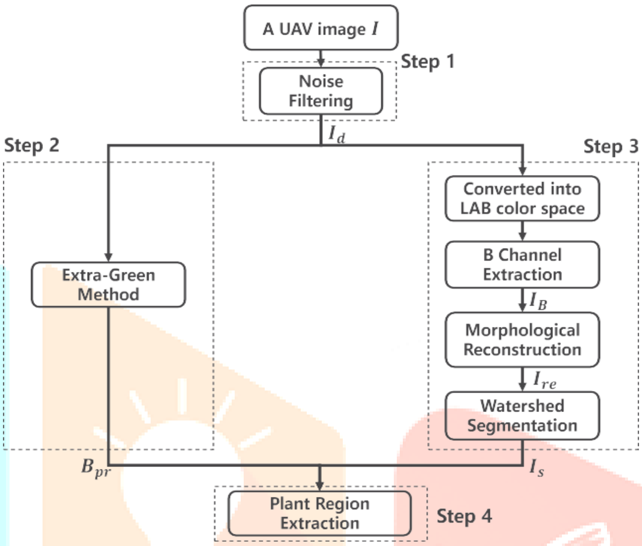


Fig: Framework of candidate tobacco plant regionextraction.

3. Plant Region Extraction:

4.

When seeking to obtain Ie successfully, one should rely on Figure 5 as an essential guide outlining each necessary step in this process. First off- numerous plant areas are isolated from available data sources as candidates for analysis; these candidates are then adjusted to meet specific required parameters before undergoing evaluation via CNN algorithms. The outcome will include an identification label distinguishing between varying sample groups- labeled as "1" when containing tobacco plants versus "0" when lacking said greenery within their borders.

In comparison to traditional neural networks, CNNs use every member of the kernel for each input position. This parameter sharing approach enables learning only one set of parameters for each new location, reducing the overall number of parameters needed. As a result, extracted features become more equivariant. For instance, a layer with 3* 3 kernels connected to a single-channel image only requires ten parameters (nine for pixels and one for neuron threshold).

As experts in our field, we have noticed an intriguing phenomenon when it comes to tobacco plants - where their central regions tend to appear brighter than surrounding leaf areas; something that can potentially aid us with identifying suitable crop growth zones using UAV imagery. To achieve this efficiently and accurately, we utilize several methods such as converting our denoised UAV Image Id into LAB colour space for better colour calibration and accuracy. We then extract the B channel image (IB) as it provides the best contrast between central and leaf areas as opposed to the lightness or A channels. To eliminate any chance of background interference within our extracted IB, we use morphological reconstruction via erosion through a marker image F - this produces an ideal final output (Ire) that is representative of candidate tobacco plant regions. To extract the plant regions from the image, we implemented a series of steps. First, we used a disk structuring element with a size of 5x5 to erode the IB image and obtain F. Next, we applied the watershed segmentation algorithm to divide the morphologically reconstructed image Ire into several candidate tobacco plant regions, resulting in our segmented image Is. Finally, we used a multiply arithmetic operation on Is and Bpr to obtain our final image for plant region extraction (IIn comparison to traditional neural networks, CNNs use every member of the kernel for each input position. This parameter sharing approach enables learning only one set of parameters for each new location, reducing the overall number of parameters needed. As a result, extracted features become more equivariant. For instance, a layer with 3* 3 kernels connected to a single-channel image only requires ten parameters (nine for pixels and one for neuron threshold).

Developing Advanced Deep Neural Networks

At the heart of our algorithm lies the need to train a complex deep CNN. This neural network comprises elementary neurons that convolve neuron weights with input volumes while transforming weighted inputs into output ones using nonlinear functions. The rectangular arrangement of these neurons determines fundamental CNN characteristics that enable them to be versatile in various computer vision tasks.

Sparse interactions are one significant attribute possessed by CNNs where every neuron only connects to a small region on its input volume or receptive field (RF). For instance, using smaller kernels helps identify meaningful features such as edges when processing images instead of all pixels. Thus, this technique allows for fewer parameters storage which significantly boosts statistical efficiency and reduces memory requirements compared to conventional fully connected neural networks. Neural networks see substantial improvement when utilizing sparse interactions. A prime example of this is seen in layers that employ 3x3 kernels and one stride; only nine neurons are required to process an image that is 5x5 and single-channel. This technique mirrors the organic patterns present in visual systems.

3. Tobacco Plant Morphology

Delving into tobacco plant morphology now
we come across two major species commonly used for commercial purposes: N. tabacum & N. rustica. These plants boast significant variety in their differing physical properties, including leaf morphology (i.e., shape, size, thickness, tip form, petiole/sessile attachment style) plant height,
and angle at which leaves attach to the stem. Additionally
tobacco plants tend to have shallow root networks consisting mainly of adventitious roots originating from the main stem. Tobacco plants boast unique leaf shapes and characteristics depending on their species. Nicotiana rustica leaves show heteroblastic development and grow spirally with even spacing; they're typically petiolate with an ovate or cordate shape featuring a dark green glossy surface. Conversely Nicotiana tabacum leaves are mostly sessile with an oblong lanceolate or ovate shape- these taller types come equipped with auricled winged petioles. While tobacco plants usually self-pollinate, roughly 4 10% of cross pollination occurs when insects carry pollen between plants. These varieties tend to flower between 55 80 days following planting; N. tabacum's inflorescence forms a terminal raceme that bears up to 150 flowers that sport perfect corollas.

When analyzing the flower of this plant species we find some distinct characteristics worthy of examination. One noteworthy aspect is its corolla system made up of fused petals forming an elongated tube culminating in five expansion lobes at the topmost point. The outer surface displays hues ranging from a pale greenish cream to pink and red tones. Each flower manages five stamens linked with the corolla tube and a pistil consisting of a lengthy slender style encompassing a two lobed stigma renowned for capturing easily adherable pollen grains. Capsule production results in narrow shaped objects that can possess various shapes such as elliptic, ovoid or even orbicular measuring around 15 18 mm long housing nearly spherical or elliptical light brown seeds inside.

Nicotiana rustica never fails to impress with its unmistakable inflorescence features that include a compact thyrse structure and yellow green corolla in addition to unique stamen lengths and an elliptic or ovoid shaped capsule holding small sized seeds within two valves. Seed production plays an essential role in understanding these plants further where Nicotiana tabacum can produce anywhere up to hundreds of thousands of seeds per plant as compared to the more modest figures seen in Nicotiana rustica, which can yield up to a quarter of this amount. With Nicotiana being part of the Solanaceae family, it's worth noting there are over 70 different identified species found worldwide.

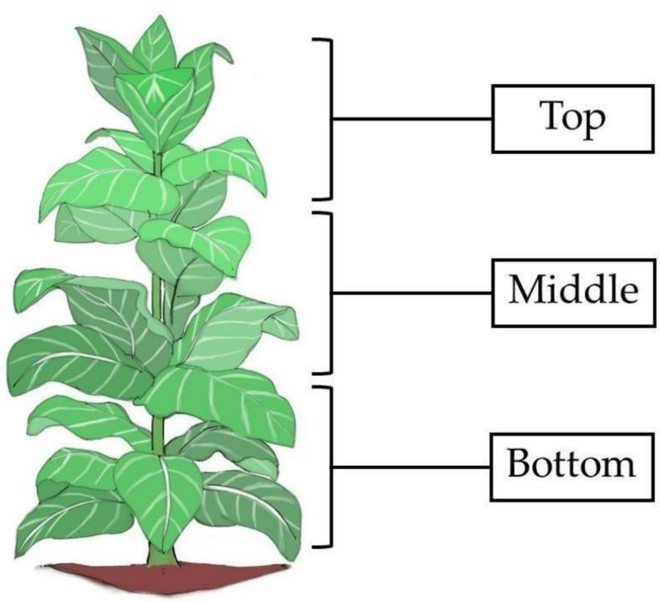
The complex genus called Nicotiana contains 60 individual plant types that can be categorized into three subdivisions: Rustica, Tabacum, and Petunioides.

Although these plants' original home was in South America surrounding areas near the Andes Mountains—some strains now thrive on Australian soil or other Pacific Islands as derivatives from their South American ancestors.

Of those many plant types within this group of tobacco like flora; only two have earned extensive worldwide cultivation efforts- Nicotiana tabacum and nicotiana rustica—two plants often grown abundantly throughout India as well.

The cultivation of tobacco in certain parts of India like U.P., West Bengal, Bihar and Assam has led to various types of the plant being present in the region. Desi types of N. tabacum boast taller plants with broader leaves accompanied by pink flowers while Vilayati & Calcuttian variations identified as N. rustica typically produce short plants with round puckered yellow leaves.

Depending on the variety used in their composition a range different tobacco product can be produced from cigarette & cigar to hookah & snuff tobaccos; all exclusively from N. tabacum strains whereas chewing based products strictly utilise those grown from the limited options available within the variant species such as those found in N. rustica cultivations; furthermore, several other Nicotiana plant cultivars exist solely for decorative purposes. In earlier times, indigenous communities like the Red Indians and Australian natives utilized specific types of Nicotiana for both chewing and smoking purposes. Of note is that there are presently 70 documented species of this plant globally; India alone conserves around 45 different kinds. A number of these types display natural pest and disease resistance qualities which scientists are incorporating into new tobacco strains known for their enhanced durability.



4. CONCLUSION

The role of plant recognition in agriculture management cannot be stressed enough as it plays a pivotal role in managing various species effectively. For researchers specializing in botany also stand to benefit from these applications' intrinsic value in medicine purposes too. When classifying these plants based on certain features extracted from images comprised our work database - we aim at identifying their species by assigning labeled classes accordingly for future reference or use where relevant cases arise again - much like how an expert would recognize them with ease by means they've previously learned over time through repeated exposure or direct observation over time! Speed mixed with accuracy represents our primary focus when developing algorithms that will enable us to detect different agricultural plants more efficiently. While techniques and methods available today for this purpose are varied, each possesses unique advantages and shortcomings. Our research suggests that the current methodologies being employed could use some refinement or enhancement moving forward. That being said, one area of potential growth lies in exploring image processing options as part of our analytical toolkit. Image processing techniques offer researchers an additional means through which we can expedite processes while equally enhancing results accuracy when studying different types of crops. More specifically, tobacco plant detection remains a pivotal factor influencing overall management within this industry. However, the majority of established practices currently rely on slow site inspections which prove less than efficient. To overcome these hurdles, the deployment of UAVs when collecting images stands out as an effective method that researchers can leverage towards achieving automated detection capabilities. These images have high spatial resolution and contain a high level of detail for the detection of tobacco plants. The main approach of this system is to recognize the different plant in agriculture environment where Speed and accuracy are the main characteristics of detection of plant. Hence, the extension of this work will focus on developing the advanced algorithms for fast and accurate detection of plants. After reviewing all above mentioned techniques and methods we can conclude that there are number of ways by which we can detect type of plants. Each has some advantages as well as limitations. Therefore, there is scope of improvement in the existing research. Image processing is a technique which helps to improve all existing research and which gives fast and accurate result of plant. Tobacco plant detection is a great significance to the management of tobacco planting. However, current methods of tobacco plant detection are based on site inspection, which is tedious and time-consuming. In order to achieve automated detection of tobacco plants, tobacco plant images are collected by means of UAVs. These images have high spatial resolution and contain a high level of detail for the detection of tobacco plants. Then, a new algorithm based on deep neural networks is proposed for the automated detection of tobacco plants in UAV images. A deep CNN is trained and established in order to classify each candidate tobacco plant region as a tobacco plant region or nontobacco plant region.

5. References

[1] L. Meng and J. P. Kerekes, "Object tracking using high resolution satellite imagery," IEEE J. Select. Topics Appl. Earth Observ. Remote Sens., vol. 5, no. 1, pp. 146–152, Feb. 2012.

[2] JIANG HUIXIAN, The Analysis of Plants Image Recognition Based on Deep Learning and Artificial Neural Network, Received March 20, 2020, accepted April 7, 2020, date of publication April 9, 2020, date of current version April 23, 2020

[3] D. R. Rossatto, D. Casanova, R. M. Kolb, and O. M. Bruno, ''Fractal analysis of leaf-texture properties as a tool for taxonomic and identification purposes: A case study with species from neotropical melastomataceae (Miconieae tribe),'' Plant Syst. Evol., vol. 291, nos. 1–2, pp. 103– 116, Jan. 2011.

[4] E. Aptoula and B. Yanikoglu, ''Morphological features for leaf-based plant recognition,'' in Proc. IEEE Int. Conf. Image Process., Sep. 2013, pp. 1496–1499.

[5] T. Ojala, M. Pietikäinen, and D. Harwood, ''A comparative study of texture measures with classification based on featured distributions,'' Pattern Recognit., vol. 29, no. 1, pp. 51–59, Jan. 1996.

[6] J. Chaki, R. Parekh, and S. Bhattacharya, ‘‘Plant leaf recognition using texture and shape features with neural classifiers,’’ Pattern Recognit. Lett., vol. 58, pp. 61–68, Jun. 2015.K. Simonyan and A. Zisserman, ‘‘Very deep convolutional networks for large-scale image recognition,’’ in Proc. ICLR, Apr.2015, pp. 1–14.

[7] M. J. Swain and D. H. Ballard, ‘‘Color indexing,’’ Int. J. Comput. Vis., vol. 7, no. 1, pp. 11– 32, 1991.

[8] J. Yang and S. Zhu, ‘‘An online image retrieval method based on self-color correlogram model,’’ J. Comput. Inf. Syst., vol. 8, no. 8, pp. 3369–3376, 2012.

[9] J.-M. Guo, H. Prasetyo, and H.-S. Su, ‘‘Image indexing using the color and bit pattern feature fusion,’’ J. Vis. Commun. Image Represent., vol. 24, no. 8, pp. 1360–1379, Nov. 2013. [11] Survey Visit to Central Tobacco Research Institute Hunsur Taluk Mysore District 571105