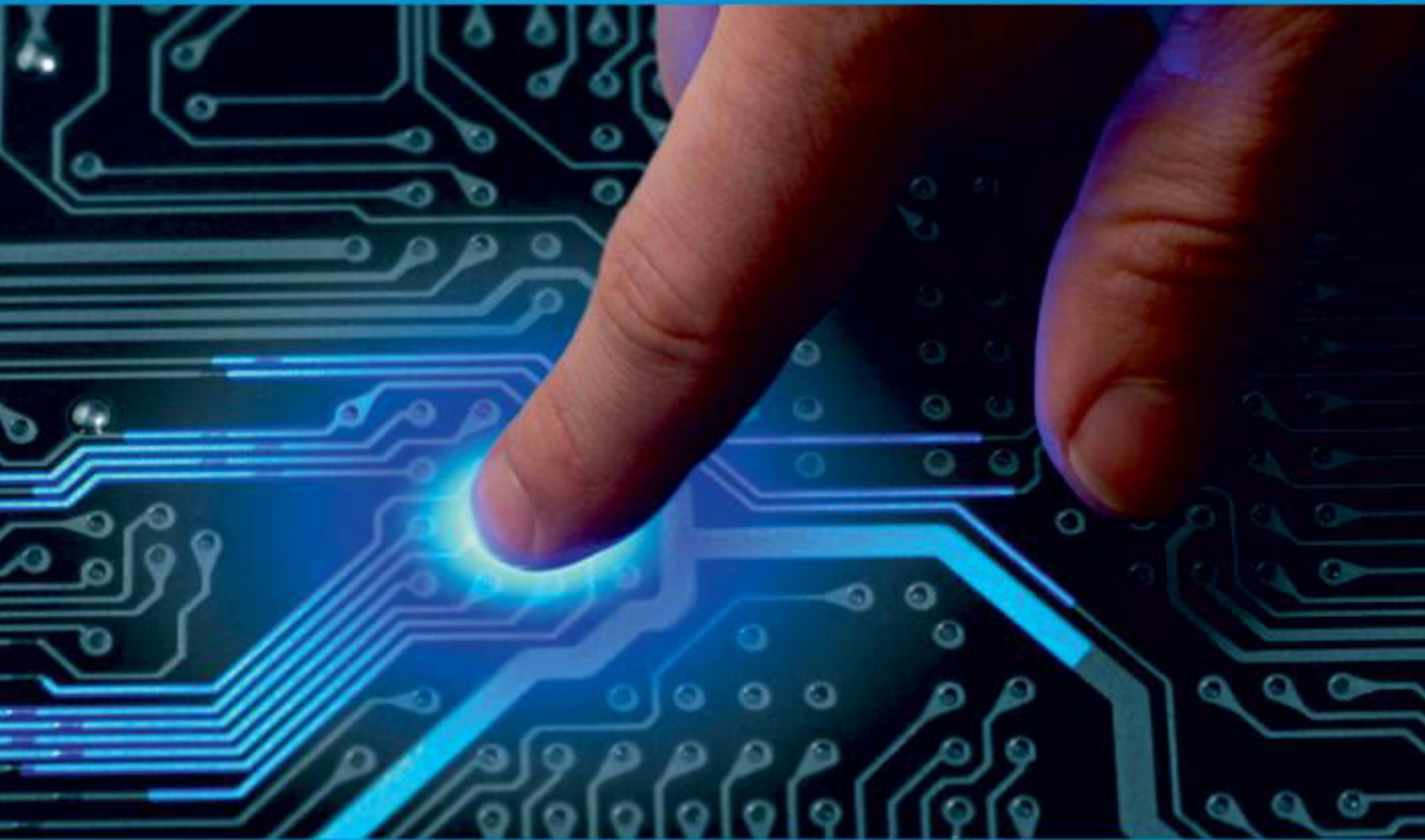
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 8, August 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165|| A Monthly Peer Reviewed & Referred Journal |

|| Volume 10, Issue 8, August 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1008040 |

Different Plant Studies Using Computers

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ABSTRACT: Species knowledge is essential for protecting biodiversity. The identification of plants by conventional keys is complex, time consuming, and due to the use of specific botanical terms frustrating for non-experts. This creates a hard to overcome hurdle for novices interested in acquiring species knowledge. Today, there is an increasing interest in automating the process of species identification. The availability and ubiquity of relevant technologies, such as, digital cameras and mobile devices, the remote access to databases, new techniques in image processing and pattern recognition let the idea of automated species identification become reality.

KEYWORDS-plant,species, computers,digital,technologies,automated,reality

I. INTRODUCTION

In plant disease study to practically verify the applicability of a new computer-vision method for discrimination between the healthy and disease infected strawberry leaves which does not require neural network or time consuming trainings. The proposed method was tested under outdoor lighting condition using a regular DLSR camera without any particular lens. Since the type and infection degree of disease is approximated a human brain a fuzzy decision maker classifies the leaves over the images[1,2] captured on-site having the same properties of human vision. Optimizing the fuzzy parameters for a typical horticultural field at a mid-day summer Mediterranean day in produced 96% accuracy for segmented iron deficiency and 93% accuracy for segmented using a typical human instant classification approximation as the benchmark holding higher accuracy than a human eye identifier. The fuzzy-base classifier provides approximate result for decision making on the leaf status as if it is healthy or not.

Computers have revolutionised the planet in many ways. Plant science is one of the fields to have benefitted from recent advances in technology, thanks to computer scientists such as Professor Tony Pridmore at the University of Nottingham, UK, who are using their computing skills to address challenges in plant biology. Tony is the director of PhenomUK, the UK's plant phenotyping network, where new software and imaging techniques developed by computer scientists and engineers, in collaboration with plant scientists,[3,5] could improve crop yields around the world

With an ever-increasing population, the world needs more food. Yet climate change and ecological destruction mean food must be produced in increasingly hostile environments. We therefore need crops that are not only more productive but are also productive in harsher conditions, with significantly less or significantly more water than before, for example.
Plant phenotyping is changing the way crops are developed by assessing how plants grow in different environments. Images of plants are captured and converted into data that can be statistically analysed, allowing researchers to determine which plants are most suitable for which conditions.[7,8,9] While plant scientists are needed to conduct plant experiments and interpret the results, the process of converting images into data requires computer scientists like Professor Tony Pridmore. A professor of computer science and head of the Computer Vision Laboratory at the University of Nottingham, Tony is also director of PhenomUK, the plant phenotyping network that aims to address issues in plant biology by bringing computer scientists and engineers into the field.
Phenotyping researchers grow plants in different experimental environments, from climate-controlled growth chambers in labs, to greenhouses and, finally, to open fields. To study them, these plants are imaged with digital cameras viewing the plants at different scales depending on what the researchers are interested in, from a whole field to an individual plant to a plant organ such as a single leaf. The large number of images required means data collection and analysis are usually automated.[10,11,12]
"Different technologies are used to take images in different environments," explains Tony. "In growth chambers, conditions are artificial so a camera can be placed anywhere." Imaging becomes more complex in greenhouses, as other objects interfere with the plant of interest, while in fields, wind and rain cause plants to move which adds further challenges. "Cameras

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taking these images may be in a fixed position, or mounted on moving platforms, drones or automated vehicles," Tony says.

As well as standard camera images, researchers also take hyperspectral images which detect features outside the range of visible light. "Hyperspectral photos can be split into hundreds of images, all showing different things, such as features visible in ultraviolet," explains Tony. The interior of plants can also be imaged, with X-ray images providing information about the plant's internal structure and magnetic resonance imaging (MRI) showing how fluids move through the plant. Standard colour images can be used to build 3D models of the plant if multiple photos are taken at different angles.[13,17,15]

Converting Plant Images Into Statistical Data

To convert images of plants into useful data that can be statistically analysed requires skills from computer science, which is where Tony's work in computer vision comes in. "An image is composed of pixels," explains Tony, "and to extract data from an image usually involves segmenting the image by writing computer code to define what the different pixels represent. For example, we might define which pixels represent a leaf so the computer can separate out all the leaves from the background of an image."

This code is no longer written by hand as machine learning means computers can now be taught to segment images and recognise objects. By marking all the leaves in a set of images and feeding them into a computer, the machine learning algorithm will develop its own rules to identify leaves in other images.

Once the computer has identified the features of the plants in the images, more code is written so the computer measures the characteristics of these features, such as leaf length, plant height or growth rate. With the images converted into numerical data, phenotyping researchers can then statistically analyse the properties of the plants. "We might do correlation analysis between genetic profiles and plants traits to determine which genes result in which physical traits in the plant," says Tony.

Phenomuk

A significant challenge for addressing global food production is that plant scientists do not often have sufficient computing skills to develop the tools they need to extract the required data from their plant experiments, while computer scientists do not have the biological knowledge necessary for answering plant-related research questions. PhenomUK aims to solve this problem by establishing collaborations between plant and computer scientists. Then, with their combined knowledge and expertise, they can find solutions to crop development together. "Plant phenotyping involves applying skills from computing to address issues in plant science," Tony explains. "Our main goal is to build a phenotyping community by bringing computer scientists and engineers into contact with plant biologists."[18,19,20]

PhenomUK also funds research projects which have components from both plant and computer sciences. One project is probing the internal structure of plants using microwave radiation, a cheaper alternative to X-ray and MRI imaging. This could be used to detect abnormalities in the internal structure of fruit or visualise underground root structures. Another project uses drones to take high quality, high frequency aerial images of wheat crops to automatically measure plant height, canopy closure and leaf area.

A recently funded project focuses on speeding up plant development by using deep machine learning to predict the future growth of plants. If software can be built to predict what a plant's roots will look like in the future, based on a series of images of the roots' growth so far, then plants will not need to be grown for as long before useful data can be collected. Another project is developing a laser scanning device which can produce high resolution 3D models of plant features. This technique could replace current imaging techniques which struggle in outdoor growing environments due to changing light and wind conditions.

The future of phenotyping

The equipment required for plant phenotyping, such as X-ray and MRI resources, is expensive. It would be uneconomical for every country to have their own equipment, which is why PhenomUK is closely related to EMPHASIS, a European research infrastructure that will share phenotyping facilities and data across Europe. This will allow researchers across the continent to contribute to the expanding field of plant phenotyping, enabling plant biologists and computer scientists to ensure crops will be able to feed the population of the future.

II. DISCUSSION

So complex are patterns and variations in the vein structures of leaves that botanists struggle to take advantage of them when trying to classify a specimen within the plant kingdom. A new study shows that computer vision technology can provide automated assistance by "learning" how to use venation to assign leaves to their proper family and order.

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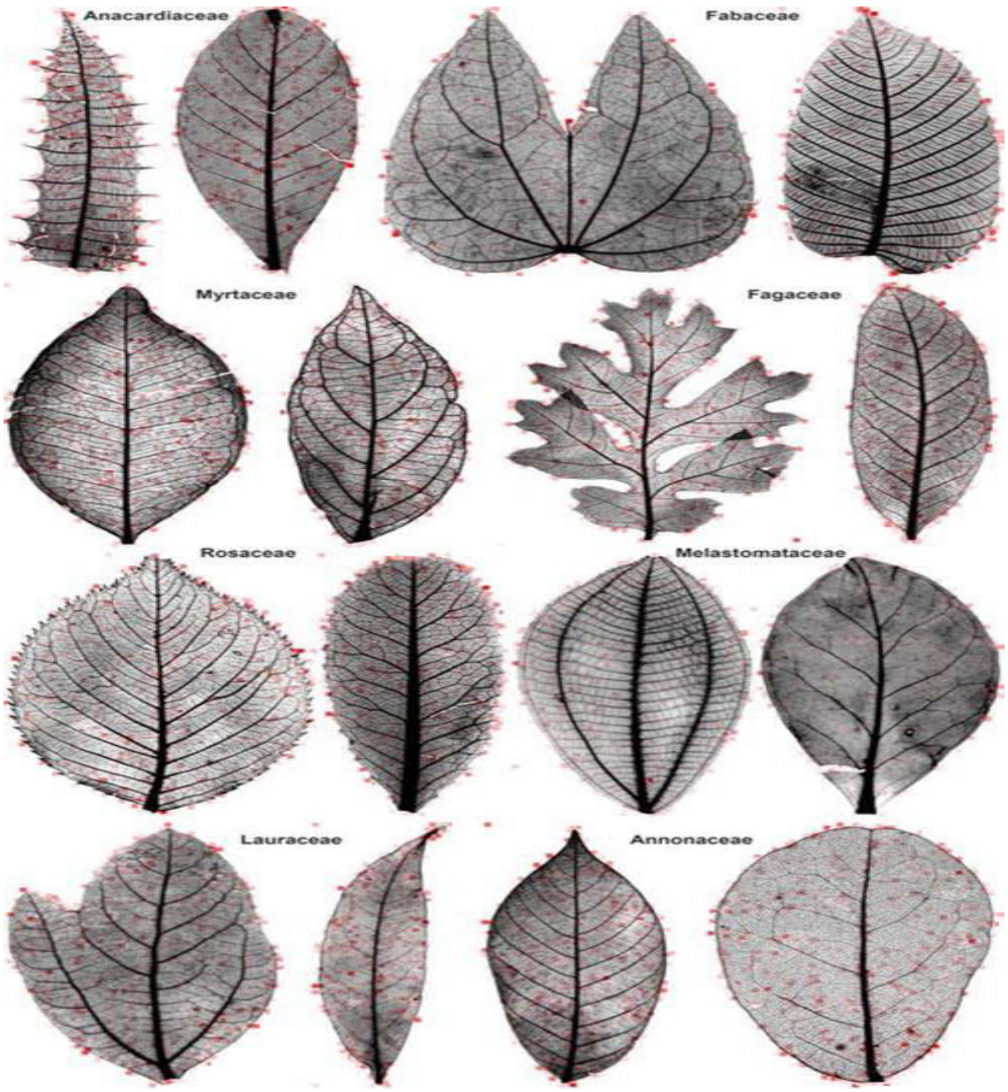

Plant patterns
Software learned to classify plants into their proper families and orders, by coming to understand key features of their shape and vein structure. Red spots highlight areas the computer identified as key. Peter Wilf/Thomas Serre

Providence, R.I. [Brown University] — About 80 percent of all the world's green plants – some 300,000 species – are those that flower, making up a vast division of the plant kingdom known as angiosperms. Given an isolated leaf, especially if preserved as a fossil, botanists can have a difficult time figuring out where it fits into the division. A new study in the Proceedings of the National Academy of Sciences suggests that computers could be a huge help.[21,22,23]

In the paper co-authored by Brown University computer vision expert Thomas Serre, researchers "trained" a machine-learning algorithm on a set of nearly 7,600 digital images of leaves that had been chemically treated to emphasize their shape and venation. The software discerned relevant patterns so well from that set of examples that it went on to identify the family of novel leaf images with greater than 70 percent accuracy (a rate 13 times better than chance) and the order with about 60 percent accuracy.

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Study lead author Peter Wilf of Penn State University said that for the Serre group's algorithms to identify family or order is "an incredible achievement." To make such classifications, the software had to come to "understand" that despite wide variations among a great many species, there were nevertheless unifying characteristics that meant that some leaves belonged to some distinct broader groups (families and orders) while other leaves belonged in others.

"Families and orders represent many thousands of species each, with incredible variation among the species, far beyond what botanists have been able to describe using the standard methods," said Wilf, a paleobotanist.

Moreover, the software visually highlighted the subtle venation features that it used to make its classifications, providing botanists with new ideas of relevant traits to consider.

"Along with the demonstration that computers can recognize major clades of angiosperms from leaf images and the promising outlook for computer-assisted leaf classification, our results have opened a tap of novel, valuable botanical characters," the authors wrote in PNAS.

Technology advances science

In his work at Brown, Serre, an assistant professor of cognitive, linguistic and psychological sciences, studies how the brain accomplishes visual perception with the goal of modeling it in computers. In studying vision both in biology and technology he has produced insights into psychology and applied technology to solve research problems. In 2010, for example, he unveiled a system for the automated monitoring of mouse behavior that has proved useful in biology studies at Brown and beyond, saving researchers enormous amounts of labor.

The new study began when Wilf invited Serre to apply computer vision to botany after reading a publication derived from Serre's doctoral work on computerized image classification in 2007. Wilf's hope was that computers could help botanists sort through massive collections of leaf fossils to determine how they may be related to modern species.

To create thousands of leaf images used in the study, Wilf's team worked for years to digitize and vet the collection, derived from the specimen holdings of the Smithsonian Institution and elsewhere.

Serre said he was excited to contribute to a novel example in which computer vision technology can aid scientific research (computer vision has been applied to leaf classification before, but it has only attempted species classification and typically relied on leaf shape). He said he has begun to strike up collaborations with Brown plant scientists such as Andrew Leslie, assistant professor of ecology and evolutionary biology, to see how else machine vision could help the field.[23,25]

"I think it can change the way we do science," Serre said. "We can do things with computer vision that would be simply impossible if we were to rely on human annotations."

At Brown, Serre worked with former postdoc Shengping Zhang on the study. Other authors are Sharat Chikkerur of Microsoft, Stefan Little of Penn State and Scott Wing of the Smithsonian Institution.

III. RESULTS

Image Processing in Leaf Pattern Recognition

Leaf pattern recognition usually follows the steps as shown below. The most challenging part of this study is to extract distinctive features of leaves for plant species recognition. In this case, different classifiers using high performance statistical approaches have been used to perform leaf features extraction and classification. The advancement in computer vision and artificial intelligence have greatly assisted researchers to classify plants through statistical modeling.

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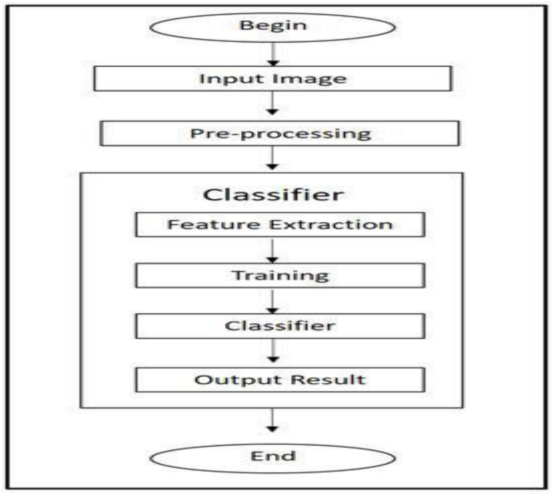

Fundamental of leaf pattern recognition.

The pre-processing step consists of image reorientation, cropping, gray scaling, binary thresholding, noise removal, contrast stretching, threshold inversion, and edge recognition. Image reorientation is aligning the input image to a standardized position, with the leaf aligned to either the x-axis or y-axis. For leaves that have the greater width: Length ratio, the length is preferably placed in the vertical or upright position [10]. To decrease the amount of computational load that is exerted upon the graphic processing unit, cropping the image is a necessary step to reduce the unnecessary foreground region of the prompt image. Turkoglu and Hanbay [11] suggested that leaf feature extraction could be done by dividing the leaf image into two or four parts, instead of extracting for the whole leaf. The proposed image processing techniques using color, vein, Fourier descriptors (FD), and gray-level co-occurrence matrix (GLCM) methods had proven to achieve 99.1% accuracy using the Flavia leaf dataset.[27,28,29]

Gray scale conversion of the image into geometrical data is implemented to optimize the contrast and intensity of images. Later, the thresholding process creates a binary image from the gray scaled image to translate the value of the image to its closest threshold, and therefore having either one of two possible values for each pixel, as presented below. Different types of noises, such as grains, and holes, could affect digital images, therefore erosion and dilation are a series of operations implemented in order to remove the background noises. The images are considered homogenous if they do not exhibit substantial differences between one another in terms of contrast stretching. These images, when shown in histogram representation, exhibit very narrow peaks. Inhomogeneity is caused by the lack of uniform lighting upon the image. The image is normalized in order to stretch the narrow range to a more dynamic range. The binary images from the process are inverted during threshold conversion, to convert the background into black. Suzuki algorithm can be utilized to extract the contours of images and further refined by diminishing the contours with small lengths with regards to its largest contour [10]. This process is known as edge recognition.

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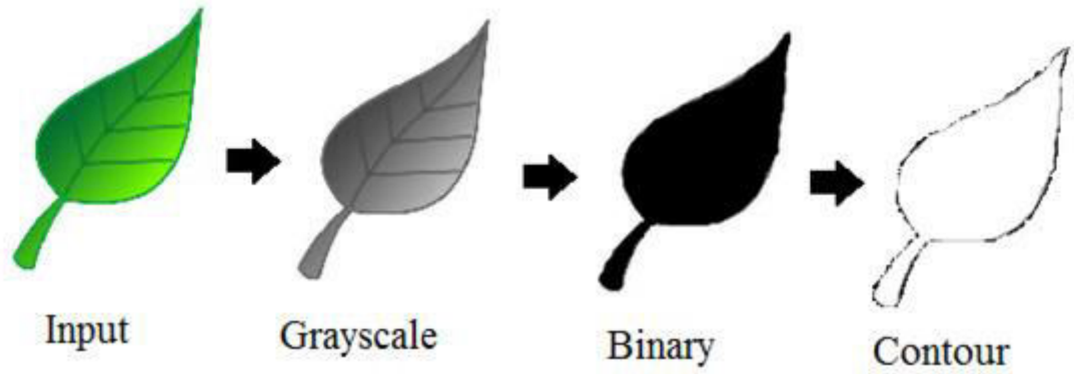

Image pre-processing stage.

Ma et al. [12] suggested that their algorithm was better than the conventional back-propagation algorithm in terms of efficiency and accuracy. They analyzed soybean leaf image to evaluate the nitrogen content by introducing median filter in their preprocessing stage. A hazier image is collected to remove grain noise, which could disrupt image processing due to high frequency properties as a result of grey difference [13]. The subsequent step would be emphasizing the leaf edge to obtain a clear image. In this case, the grey linear transformation technique is used to further add the difference in grey saturation between the leaf image and the background, and thus enhance the image by gaining a comparable threshold value of sample image and background to decrease error rate [14]. Since the image background still has an undesired value, the image is binarized to remove the background value completely before the original image is imposed to the processed image [15]. The output of this preprocessed image had successfully analyzed the nitrogen content of soybean based on colour characteristics [12].

Bo et al. [16] used the Hu moment invariant for soybean leaf recognition in image processing to distinguish its leaf feature from weeds. Chronologically, they procured the real time image with a camera as the input data which was then converted to grayscale with 2G-R-B [16]. The data of both leaves from soybean and weed was then further processed by erosion algorithm to remove distortion. The next step involved the Hu moment invariant adopting the 16 × 16 template to declare the invariability of soybean leaf image including rotation, scale, and translation. Succeeding the preprocessing stage would be the identification process, in which the nearest neighbour classifier was used to compare the relative soybean leaf image via its respective markings. The accuracy of the classification along with the image preprocessing could yield 90.5% recognition rate [16].

Grand-Brochier et al. [17] made a comparative study between different types of image preprocessing techniques to analyze the effectivity of each method, in addition to colour distance map and input stroke. The local color, which is the color of the subject with the whole image was matched. One of the methods is simple linear iterative clustering (SLIC), which utilizes super-pixel to cluster them with a predetermined value through repetitive iteration of the nearest neighbor, so that only the data vector with similar value is included [17]. The results of SLIC technique yielded 87.4% precision [17]. Guided active contour (GAC) is another method. In GAC, the Snake segmentation technique is adopted where the initial stage involves iteration to improve the polygonal framework for the elongated leaf shape [18]. This iteration derives an energy equation to guide the polygon to expand within its closed area [19]. The GAC technique managed to procure precision up to 95.2% [17].

In Kurtz algorithm, a hierarchical approach was used to extract segments of interest from the lowest to the highest resolution data, which was the first cluster image material sharing the common colour properties into a group of coarse image patches [20]. The individual patches are depicted as hierarchical construct with a binary partition tree (BPT). This cluster of images can be assumed to be like a forest of BPTs. When the construction of this forest is completed, each tree will be gradually segmented. Eventually, the progressive segmentation will produce a global segmentation of the image. This method could produce precision up to 85.1%. The data of Kurtz algorithm only utilized colour distance map without input stroke as opposed to the two previously reported methods; SLIC and GAC [21].

A comparative result had been established using power watershed for preprocessing of the image. Power watershed used the concept of magnitude reduction to get more accurate data from the adjacent region, which is identical to the

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Graphcut method, hence improving segmentation of the image. Power watershed technique included multi labelling, contrast, and ratio invariant stage [22]. The Power watershed method compared to the Graphcut technique yielded 63.5% precision.

The discovery of various preprocessing techniques has proven to vastly facilitate the development of an effective machine learning. Since visual-based machine learning depends on how well the feature of a certain image is extracted from the preprocessing stage, it is crucial to understand the desired outcome in preprocessing stage. This is because different problems require different solutions or approaches. Additionally, different situations will present different images, and the preprocessing stage of the predetermined image would revolve around the enhancement of the subject features.

IV. CONCLUSIONS

A computer vision approach which can completely neglect the background of the image is speeding up the recognition process and it is suitable for highly complex plant leaf samples. A system that neglects distortion tremendously enhances the recognition technology and even makes the recognition of aquatic fauna more feasible since aquatic plants or algae may not have a definitive shape. The current image processing technique should be robust under diverse intensity of lighting. This new algorithm can be developed by tweaking the detection technique which may lead to detection of specific diseases. The advantage can also be applied for herbal plants recognition to prevent adulteration for better quality control, especially for product efficacy and safety.[30]

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