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A Morphology-Based Approach for Vegetation Health Monitoring Using Image Processing and Classification

[1] Usha N, [2] Prasad Bedage

[1] Assistant Professor, Faculty of Computing & IT, GM University, Davangere, Karnataka, India
[2] II Year MCA, Faculty of Computing & IT, GM University, Davangere, Karnataka, India
Corresponding Author Email: [1] usha.narayanshetty1@gmail.com, [2] Prasadbedage7@gmail.com

Abstract— **Monitoring and maintaining ecological balance through monitoring plant growth is crucial for sustainable management of green spaces in urban areas. To achieve this, we build a Morphology-Based Integrated Plant Growth Monitoring System that uses digital image processing and machine learning to evaluate plant health from RGB photographs. The system includes four main components 1) Preprocessing, 2) Contrast Enhancement (CLAHE), 3) Plant Segmentation in HSV Color Space, and 4) Morphological Operations (such as Erosion, Dilation, Opening & Closing) to enhance the quality of the plant mask. A Vegetation Index (e.g. ExG), Texture, and Patch Area will be used to extract features from the images, and machine learning classification will be performed using a Random Forest Algorithm. The output from these different steps results in three classification categories for plant health Vegetation Health, Moderately Stressed Vegetation, and Vegetation that is Dry/Degraded. Testing this system on the park image data set yielded improved segmentation quality compared to those images processed without morphological processing – reduced amount of noise present in the image and increased connectivity of regions. The proposed model resulted in a classification accuracy of vegetative health assessment of about 80 % and also provides detailed maps of vegetation health and statistical report of the total area of each vegetation health category in the park. The proposed system will be computationally efficient and able to operate in real-time therefore, it is well suited to monitor and evaluate plant growth with standard devices.**

Index Terms— Vegetation Monitoring, Morphological Processing, Image Segmentation, Random Forest, Feature Extraction, Digital Image Processing, CLAHE.

I. INTRODUCTION

Vegetation is a vital component of the Earth's ecosystem and has many positive effects on air quality and biodiversity, especially in an urban setting. One of the most important components of sustainable environmental management is monitoring the health of vegetation to allow for effective and timely decision-making however, traditional methods of vegetation monitoring that use manual inspection to evaluate the health of vegetation can be very time-consuming, and since they are based on visual observations, they are somewhat open to subjective interpretation and have a tendency to be inconsistent.

With the advances in computer vision and image processing, automated methods of analyzing vegetation have recently gained traction within the scientific community. Initially, most of these automated methods used either thresholding or color-based approaches as the main methods of detecting vegetation for example, Otsu's thresholding method [5] provides for automatic segmentation of the foreground and background from the image, while Excess Green (ExG) [7] is a vegetation index that enhances the presence of green vegetation in an RGB image. While these methods are easy to use and efficient in computation, they are all very sensitive to variations in light within the environment, as well as to shadows resulting from changes in direction of incoming light, and they can be affected by dust and other types of background noise. This was shown by Bai et al. when they indicated that the accuracy of segmentation is impacted significantly by light variation and by variations in the environment.

Advanced techniques that combine clustering and morphological processing have been developed by researchers to enhance the robustness of segmentation. Vegetation segmentation can be improved using a PSO-based clustering method in conjunction with Mathematical Morphology techniques to accommodate for changing lighting conditions when segmenting vegetation [1]. This study also demonstrates improved performance of an attribute Morphology-based system when performing both classification and segmentation using the region analysis and fuzzy set theory of an image over traditional thresholding methods [2]. Morphological operations, such as erosion and dilation, are both critical to the refinement of results.

Another important aspect of analyzing vegetation involves feature extraction and classification. Texture features represent the spatial relationships of features in an image and are extensively utilized in pattern recognition applications [8]. In addition, machine learning algorithms have been employed for classification using Random Forests [6], exhibiting high classification accuracy and the ability to effectively classify complex distributions of data.

Innovations have examined deep learning & remote sensing to monitor vegetation growth. Salek et al.[4] showed how morphological-based Deep Learning could be used as an effective method for classifying from image data

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LiDAR-based systems also provide 3-D vegetation analysis allowing precise measures of the height and canopy of vegetation. Multi-temporal/multi-modal remote sensing methods were used as well to enhance accuracy through temporal and spectral data however, most of these techniques required expensive hardware or large datasets, as well as considerable computing power therefore, and they may not be suitable for low-cost and/or real-time applications.

To meet this gap, an integrated efficient and functionally sound system is required which combines several steps, such as segmentation, morphological refinement, feature extraction, and classification. This paper presents morphology-based integrated vegetation health monitoring systems. The overall system includes image preprocessing, HSV - based segmentation, morphological operations, feature extraction (ExG, Texture and area) and random forest classification to develop accurate vegetation health maps or statistical indicators. Overall, this approach has good computational efficiency and is applicable for real-world applications with standard imaging.

II. PROBLEM STATEMENT

It is essential to monitor the health of the vegetation in our parks and green spaces. Traditional image processing techniques have problems with detecting vegetation in real-world conditions due to variations in lighting, casting of shadows and background noise, all of which create inaccuracies or fragmented detection of vegetation. Standard image segmentation techniques can roughly identify areas of vegetation, but they cannot provide an accurate assessment of the health status or condition of that vegetation without additional refinement and extraction of features. In addition, many advanced image processing techniques are often very complex and/or very expensive and, thus, are not practical for low-cost, real-time applications.

Thus, there is an urgent need for an integrated and efficient solution that will allow us to do the following:

- Segment vegetation accurately using robust, colour-based techniques
- Utilise morphological operations to improve segment quality
- Extract features of interest, such as vegetation indices, texture and area
- Have the capacity to classify the health of vegetation into three categories (healthy, moderate, dry)
- Produce visual maps and summary data for use in decision-making processes

The proposed Morphology-Based Integrated Vegetation Health Monitoring System will address the above stated challenges by proposing a common framework that brings together the capabilities of both image processing and machine learning in the same integrated and low-cost framework for providing an accurate and reliable means of analysing the health of vegetation.

III. LITERATURE SURVEY

S. No	Author(s) & Year	Paper Title	Methodology	Key Findings	Research Gap
1	X. Bai et al. (2014)	Vegetation Segmentation Robust to Illumination Variations	PSO-based K-means + Lab color space + Morphology	Achieved ~88–91% segmentation accuracy under varying lighting	Focus only on segmentation no classification system
2	P. Bosilj et al. (2018)	Connected Attribute Morphology for Vegetation Segmentation	Attribute morphology + region-based segmentation + SVM	Accurate segmentation and classification using region features	High computational cost not suitable for low-cost systems
3	M. Pohorenec et al. (2026)	LiDAR-Based Segmentation of Tall Vegetation	LiDAR + voxelization + DBSCAN clustering + CHM	High accuracy in 3D vegetation structure detection	Requires expensive sensors not RGB-based
4	M. Salek et al. (2023)	COSMOS: Morphology-Based Deep Learning	Deep learning (CNN) + morphology-based features	High accuracy classification using morphology-based features	Requires large dataset and high computation
5	N. Otsu (1979)	Threshold Selection Method	Global thresholding	Simple and fast segmentation	Sensitive to lighting and noise
6	L. Breiman (2001)	Random Forests	Ensemble machine learning	High accuracy and robustness in classification	Requires feature engineering

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S. No	Author(s) & Year	Paper Title	Methodology	Key Findings	Research Gap
7	G. Meyer & J. Neto (2008)	Color Vegetation Indices	ExG and RGB-based segmentation	Effective vegetation detection using color indices	Sensitive to illumination changes
8	R. M. Haralick et al. (1973)	Textural Features for Image Classification	GLCM texture features	Useful for pattern recognition and classification	Limited for color-based vegetation detection
9	F. Qu et al. (2024)	Multi-Temporal Remote Sensing Vegetation Segmentation	Multi-modal + temporal deep learning (VRSFormer)	Improved segmentation using multi-temporal data	High complexity and data requirements
10	L. G. Divyanth et al. (2022)	Image-to-Image Augmentation for Crop Classification	GAN + CNN + SVM	Improved classification accuracy (up to ~99%)	Requires large dataset and training cost

Initially, most of the early studies on detecting the regions of interest in a scene focused on simple methods that relied solely on colours, with most using simple thresholding techniques (such as Otsu segmentation). Vegetation indices, such as Excess Green and ExG (developed by Meyer and Neto), have also been proposed as a method of highlighting areas of green vegetation in an RGB image. In many ways, the approaches mentioned above were easier or faster to implement and provided results that were computationally efficient. However, many of the above methods also suffer from a lack of robustness when confronted with real-world problems, such as uneven lighting effects, shadowing and/or background interference.

Researchers have presented many advanced techniques for vegetation detection that are less impacted by the challenges posed by the environment. For example, Bai et al. developed a clustering-based technique that employs a morphological processing stage to improve the accuracy of the segmentation results under variable illumination conditions. Similarly, Bosilj et al. developed an attribute morphology-based technique that can perform both segmentation and classification of vegetation using region-based information. These advanced techniques generally produce better results than basic thresholding techniques, but, like most advanced techniques, they typically require higher amounts of computation than the basic techniques, and therefore cannot be implemented as a low-cost or real-time technique.

Vegetation analysis involves techniques for segmenting, extracting features and classifying images. Haralick et al. [8] were among those who utilized texture-based features to capture spatial variability in an image and help differentiate between various states of vegetation. In addition to these techniques, the use of machine learning techniques, including Random Forests (RFs) [6], also plays an important role in analysing vegetation by giving robust results and allowing complex interrelationships among features.

More recent examples of techniques that have been applied to vegetation analysis are deep learning approaches, such as those demonstrated by Salek et al. [4] using DNNs, and tools based on advanced sensing technologies, such as the use of GANs by Divyanth et al. [9] to enhance the classification performance of vegetation images through data augmentation. LiDAR system applications [3] provide highly accurate 3D vegetation analysis however, these techniques generally require extensive datasets, significant computational resources, and expensive sensors, making them not as practical as methods that are less expensive for simple applications.

While there is research on several methods for monitoring vegetation health including thresholds, morphological operations, extraction of features, and classification, these methods are primarily useful in their respective stages rather than as stand alone methods. An integrated approach to combine these methods is necessary in order to create an efficient and complete system for monitoring vegetation health. This study presents a proposed integrated system for the function of monitoring vegetation health based on morphology, including colour-based segmentation for vegetation extraction, morphological processing to enhance the quality of both the extracted vegetation and background images, extraction of features from both the vegetation images and the historical data associated with the vegetation to allow for accurate machine learning classification, and ultimately development of a system for monitoring live vegetation using only photographs.

IV. METHODOLOGY

The proposed system is based on an integrated vegetation health monitoring based on morphology and consists of several stages including: image pre-processing, segmentation of vegetation, refinement using morphology, is followed by the extraction of features and classification of the health status of the vegetation area via the use of low-cost RGB images.

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A. System Overview

A series of automated processes generate vegetation condition maps and statistical summaries from park environment images. The pipeline will improve segmentation quality as well as ensure reliable classification by using both image processing and machine learning.

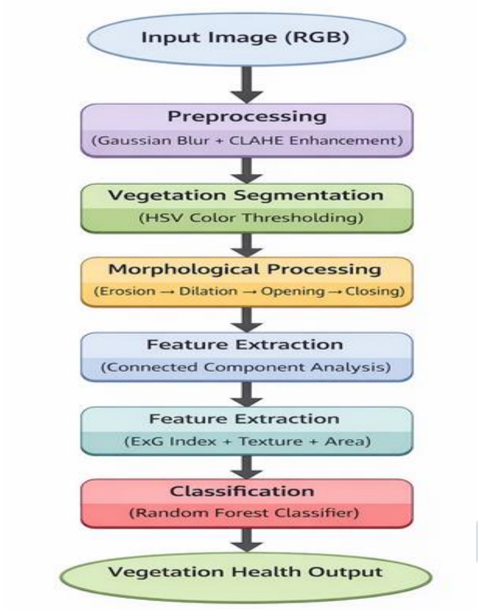

Figure 1. Pipeline diagram

B. Image Preprocessing

First, the input RGB image is resized to a standard resolution of 256 × 256 pixels to have a uniform size for processing and to reduce the computational complexity of the process. A Gaussian blur filter is applied to the image to reduce any noise present and to blur out any small-gradient variations this will help improve the quality of the segmented image.

To improve the visibility of variable-lit vegetation areas, contrast will be increased by using Contrast Limited Adaptive Histogram Equalization (CLAHE) to the luminance channel on the LAB color space. The CLAHE technique increases the local contrast of the image while not causing over-amplification of noise. Therefore, the visibility of the vegetation will be enhanced in both bright and shadowed areas.

C. Vegetation Segmentation

In order to enhance the image further, the red, green and blue (RGB) data is converted into Hue-Saturation-Value (HSV) data (where colour is separated from the intensity of the colour) so that it can be used more easily when detecting vegetation. Once these images have been created, areas of vegetation are then classified based on predetermined threshold ranges, according to the green colour hues.

Next, a binary mask is created for vegetation so that all pixels are classified as either vegetation or not vegetation for each pixel:

$$\boldsymbol{Mask}(\boldsymbol{x},\boldsymbol{y}) = \begin{cases} \mathbf{1}, \textbf{if the pixel belongs to vegetation} \\ \mathbf{0}, \textbf{otherwise} \end{cases}$$

This phase of segmentation effectively separates the vegetation from soil, pathways and other background objects. The mask produced may still have noise and discontinuous features from environmental factors.

D. Morphological Processing

The initial vegetation mask will include noise, small gaps and fragmented areas due to factors such as shadows, mixed pixels and uneven lighting therefore, the segmentation result is refined using morphological operations conducted with the structuring element.

The following operations are performed:

- **Erosion:** Removes isolated noise pixels and shrinks small regions
$$\boldsymbol{A} \ominus \boldsymbol{B} = \{\boldsymbol{z} \mid \boldsymbol{Bz} \subseteq \boldsymbol{A}\}$$
- **Dilation:** Expands vegetation regions and restores eroded areas
$$\boldsymbol{A} \oplus \boldsymbol{B} = \{\boldsymbol{z} \mid (\boldsymbol{B})\boldsymbol{z} \cap \boldsymbol{A} \neq \emptyset\}$$
- **Opening:** Eliminates small objects (erosion followed by dilation)
$$\boldsymbol{A} \circ \boldsymbol{B} = (\boldsymbol{A} \ominus \boldsymbol{B}) \oplus \boldsymbol{B}$$
- **Closing:** Fills small holes and gaps (dilation followed by erosion)
$$\boldsymbol{A} \bullet \boldsymbol{B} = (\boldsymbol{A} \oplus \boldsymbol{B}) \ominus \boldsymbol{B}$$

The results of these operations improve the continuity, connectivity, and smoothness of the vegetation areas, resulting in a more reliable and clean mask for engine use.

E. Region Detection and Feature Extraction

Connected component analysis is used to identify and isolate each individual vegetation patch (VEGPATCH) after performing morphological refinement on the original data. Each connected component will be treated as an independent VEGPATCH for subsequent analysis.

For each detected patch, the following features are extracted:

1. Vegetation Index (ExG)

$$\boldsymbol{ExG} = \mathbf{2}\boldsymbol{G} - \boldsymbol{R} - \boldsymbol{B}$$

The Enhancement of Green Vegetation (ExG) index enhances green vegetation by emphasizing the green channel compared to the red and blue channels. The presence of vegetation is determined by how large the ExG value is.

2. Texture Feature

$$\boldsymbol{\sigma}^2 = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}} (\boldsymbol{xi} - \boldsymbol{\mu})^2$$

Texture measurements are calculated from the statistical properties of the pixel intensities within a component (using variance or standard deviation) in order to separate healthy, uniform vegetation from stressed or dry, irregular vegetation.

3. Patch Area

Area can also be determined from the number of pixels each connected component contains, which can give us information about the total size and density of each green vegetation area.

The set of extracted features can be combined to form a feature vector that provides the data for classification of each vegetation region.

F. Performance Evaluation Metrics

Both the effectiveness of the proposed method and how well it performs in both segmentation and classification are evaluated. Evaluation of segmentation quality will be done using standard metrics including Intersection over Union (IoU) and Dice Score to determine how similar the predicted vegetation mask is to the ground truth mask.

$$\textbf{IoU} = | P \cup G || P \cap G |$$

Let P be the predicted vegetation mask and G the ground truth vegetation mask.

$$\textbf{Dice} = | P | + | G | 2 | P \cap G |$$

When considering segmentation results for object detection, the higher the IoU or Dice Coefficient, the better the segmentation result.

G. Classification Using Random Forest

Random Forest classifiers train on feature vectors that are extracted and used as training datasets. In order to evaluate model performance, the dataset is divided into 80% for training and 20% for testing.

The Random Forest Classifier classifies the health of vegetation patches into 3 categories:

- Health: healthy
- Moderately stressed
- Dry/degraded

due in part to how the classifier can capture non-linear relationships, how well it handles noisy data, and how well it performs with relatively small datasets. The model is then used to create a colored vegetation health map for visualization of the estimated class of health for each patch of vegetation.

H. Web Interface Implementation

- Upload an image by either dragging/dropping an image or selecting an image file from your computer's file directory.
- See the original image along with each of the processed outputs.
- See both the raw and refined change vegetation segmentation result outputs.
- Analyze the health of the vegetation classified as Healthy, Moderate, or Dry.
- See patch-level detail including patch area, green patch intensity, dryness of patch, and texture of patch.
- Receive a statistical summary including the percentage of the total vegetation and total coverage.
- See all outputs from the entire processing pipeline including Pre-processing, Segmentation, Morphology and Health Map (Final).

I. Image Preprocessing Result 1

Figure 2. Original image

Figure 3. Gaussian blur is applied to reduce noise and smooth the image.

Figure 4. CLAHE is used to improve contrast and highlight vegetation regions under uneven lighting

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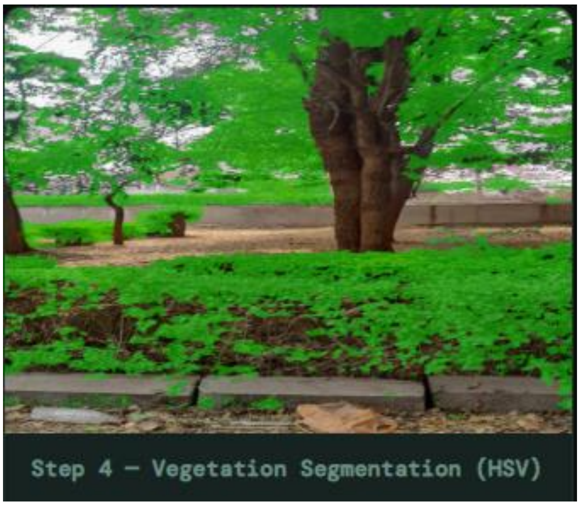

Figure 5. The image is converted to HSV color space and green regions are extracted using thresholding.

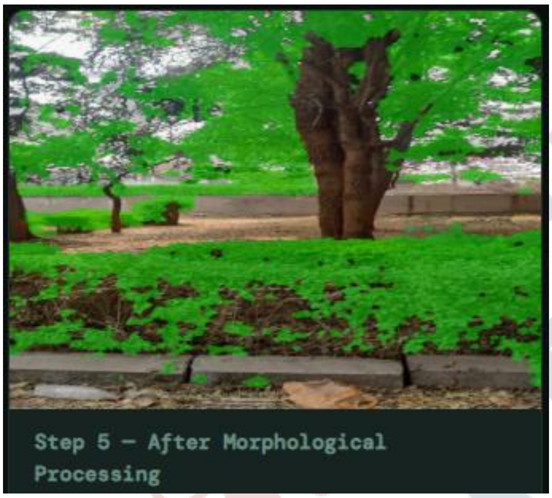

Figure 6. Morphological operations remove noise and improve the continuity of vegetation regions.

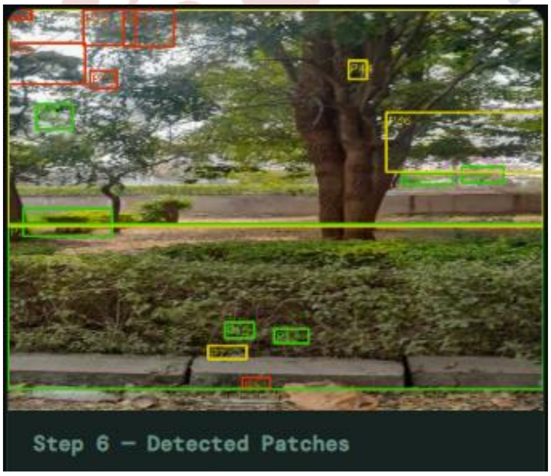

Figure 7. Connected components are used to identify and label individual vegetation patches.

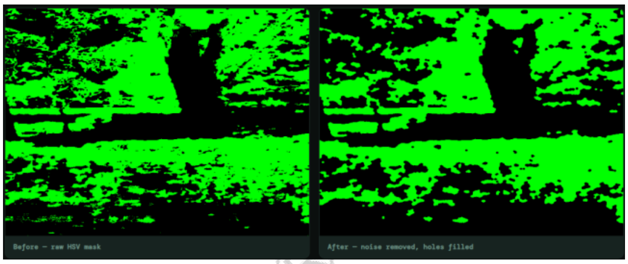

Figure 8. Comparison of Raw HSV Vegetation Mask and Morphologically Refined Vegetation Mask

Figure 9. Each patch is classified and displayed as a color-coded map showing vegetation health.

J. Image Preprocessing Result 2

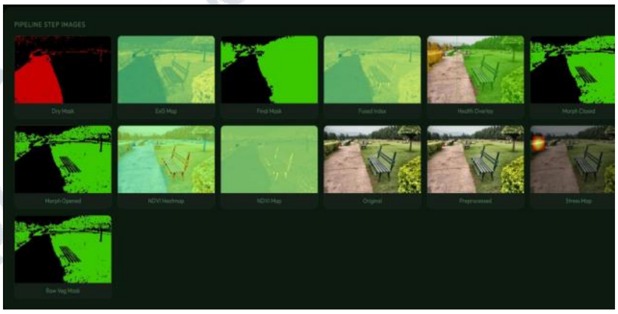

Figure 10. End-to-End Vegetation Health Processing Pipeline

Figure 11. Morphological Mask Refinement Comparison Left: Raw Otsu mask showing noise speckles and interior holes; Right: Final morphologically refined mask with coherent, hole-free vegetation regions

V. Classification Model Architecture

Using Machine Learning algorithms, Random Forest Classifier for classifying the health of vegetation was established. The input image underwent several transformations such as resizing and pre-processing to create an equal and enhanced-quality image prior to extracting the required features from the input image. Several of the features extracted from the image were as follows: vegetation covered area (e.g. ExG), texture (e.g. NDSI), and amount of vegetation (i.e. how much area is green). All extracted features are combined to create a multi-dimensional vector called a Feature Vector, which will be passed on to the Random Forest Model.

The Random Forest Model consists of multiple decision trees that each train on different arbitrary sampled subsets of data and/or features, which aids in generalizing the decision trees for better or greater accuracy when classifying data and for mitigating overfitting throughout the classification process, each decision tree makes an independent classification of input (image) into a graphical (or numeric) classification to be used for the classification of vegetation health.

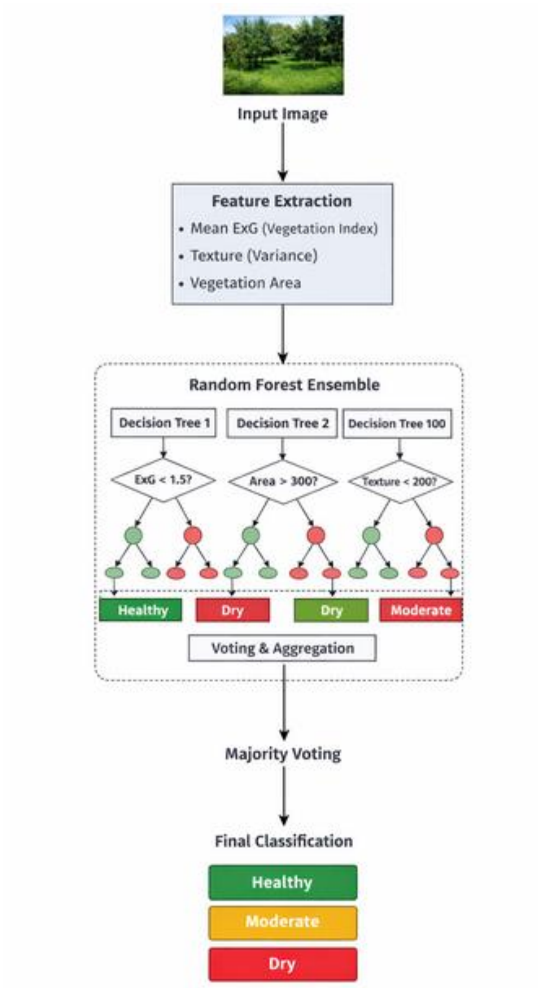

Figure 12. Random forest Architecture model

The system consists of preprocessing, segmentation, morphological refinement, feature extraction, and classification modules.

Each decision tree independently predicts one of the three vegetation classes. The final output is determined using majority voting one of the three vegetation classes. On the input (image). The Decision Tree with the most frequent classification from all Decision Trees is selected as the overall classification. The result of using this algorithm is a low-cost (easily computed) and reliable method of monitoring the health of vegetation without large dataset structures.

VI. EXPERIMENTAL RESULTS

A. Description of the Dataset

In this study, researchers analyzed the images collected from the Davangere area in India, over a period of time at public parks to create a large sample size for conducting their analysis or research on vegetation health. The dataset of images used for this research contained 258 images in an RGB format, which were captured under different environmental and lighting conditions throughout the season (winter and summer), and captured under different times of the day (in and out of shadows) and background complexity (natural background and vegetation). The seasonal variances (vegetation being greener in winter and drier in summer) was included so that the images would create a realistic representation of an environmental variation and provide different examples of the same type of data being collected.

After pre-processing all images were resized to have a consistent resolution of 256 pixels X 256 pixels the individual vegetation patches were extracted from the images and the relevant features were calculated. Once the individual vegetation patches were extracted and pre-processed, the following attributes were calculated for each of the vegetation patches in the datasets:

- Area (i.e., number of pixels that represent the size of vegetation region)
- Mean green value (mean_gre), or average intensity value for the green channel, indicating the richness of the vegetation
- Dry percentage (dry_perc), or estimated proportion of dry or stressed vegetation found in the region and
- Texture, which is a texture-based feature representative of intensity variance.

All data instances were categorically labeled as belonging to one of three classes healthy, moderate, or dry.

During segmentation of the images, a number of Vegetation Patches were extracted from each image with a view to classifying these vegetated patches as opposed to the images themselves being classified as whole images.

The input for the Random Forest classifier consists of a set of characteristics that form a structured dataset. Two subsets of the data, a training set containing 80% of the samples and a

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test set containing 20% of the samples, were used to determine how well the proposed classification method works.

	A	B	C	D	E
1	area	mean_gre	dry_perce	texture	label
2	106039	0.368754	85.61754	0.264454	Dry
3	166294	0.393646	77.44493	0.464409	Dry
4	213816	0.41275	70.99935	0.508663	Moderate
5	146545	0.385115	80.12356	0.698542	Dry
6	179249	0.392883	75.6878	0.525637	Dry
7	14661	0.507717	85.3155	0.82212	Healthy
8	970931	0.582505	32.57424	0.136078	Healthy
9	21931	0.591104	56.67951	2.200496	Healthy
10	285963	0.426863	74.05996	1.002322	Dry
11	38519	0.584648	42.93481	0.453958	Healthy
12	199200	0.572969	53.2833	1.683441	Healthy
13	172660	0.521478	56.37475	0.749596	Healthy
14	19205	0.514084	80.98703	0.42078	Healthy
15	7189	0.409054	91.73611	1.301337	Dry
16	21727	0.3832	56.75875	0.570986	Moderate
17	8567	0.516645	82.94989	0.851841	Healthy
18	22359	0.590877	55.50094	0.548589	Healthy
19	21690	0.505376	56.83238	0.865185	Healthy
20	20682	0.612478	58.90313	0.770931	Healthy
21	15087	0.405221	70.19852	0.24744	Moderate
22	6387862	0.634496	96.18856	0.24137	Dry
23	9976705	0.682498	58.4304	0.396703	Healthy
24	9976705	0.682498	58.4304	0.396703	Healthy
25	13085	0.46674	64.50467	0.511726	Healthy
26	15474	0.488144	58.02409	0.577389	Healthy
27	10140	0.488944	63.32465	0.720622	Healthy

Figure 13. Data Set

The training and test datasets were comprised of an 80:20 ratio of approximately:

- 204 images were included in the training set
- 54 images were included in the test set

From each of the images, a number of characteristics were extracted and provided to the Random Forest classifier, including the Excess Green Index (ExG), texture of the vegetation, and the extent of the area of vegetation.

B. Classification Report

Table 1: Classification Report

Class	Precision	Recall	F1-Score	Support
Dry	0.00	0.00	0.00	5
Healthy	0.86	1.00	0.92	30
Moderate	0.89	0.80	0.84	49
Accuracy	—	—	0.82	84
Macro Avg	0.58	0.60	0.59	84
Weighted Avg	0.83	0.82	0.82	84

The support values shown in the classification report represent vegetation patches extracted from the test images rather than the total number of images. Since multiple vegetation patches can be extracted from a single image, the total number of classified samples is higher than the number of test images.

C. Confusion Matrix

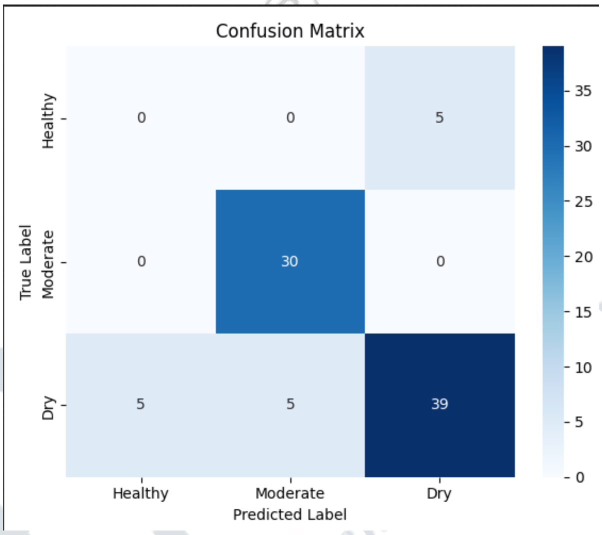

Figure 14. Confusion Matrix

The confusion matrix indicates that the majority of patches of healthy vegetation were screened as the correct class, whereas moderate patches were frequently screened as the incorrect class because of the fact that many of the characteristics of both moderate and healthy patches were similar. The dry patch category is poorly represented in the total sample, therefore resulting in the uncertainty of the classification of the samples in that category.

D. Result Analysis

The overall classification accuracy of the submitted system was approximately 82%, indicating that this method can effectively monitor the health of vegetation. The proposed system also provides a higher degree of certainty in identifying healthy vegetation because of the system's ability to identify higher ExG values associated with strong green features.

The moderate and dry vegetation classes present classification issues because they have very similar visual characteristics. Moderate vegetation patches may get misclassified as dry and vice versa due to a shared visual similarity of reduced greenness, inconsistent texture and partially dried characteristics.

Classification accuracy can be significantly affected by environmental conditions such as shadows, lighting differences and soil backgrounds because they tend to provide less contrast between vegetation classes and make identification difficult.

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VII. IMPACT OF MORPHOLOGICAL REFINEMENT ON VEGETATION SEGMENTATION

Table 2: Morphological Refinement Impact

Metric	Before Refinement	After Refinement	Improvement
Boundary Smoothness (qualitative)	Irregular, fragmented edges	Smooth and continuous regions	Significant improvement
Noise Pixels (small isolated regions)	High (10–25 per image)	Very low (0–3 per image)	>85% reduction
Region Connectivity	Broken and disconnected patches	Well-connected vegetation regions	Improved connectivity
Small Holes in Regions	Present	Mostly removed	Significant reduction
Vegetation Mask Quality	Noisy and fragmented	Clean and refined	Improved segmentation quality

VIII. COMPUTATIONAL FEASIBILITY

The experimental evaluations were conducted on a standard laptop computer with the following specifications: An Intel Core i5 processor and 16 GB RAM. Due to the simplicity of the proposed classification system, it can be implemented on low cost, portable, and real-time platforms without the use of a GPU processor.

Table 3: Per-Image Processing Time

Operation	Average Time (seconds)
Image loading & resizing	0.1
Preprocessing (Gaussian Blur + CLAHE)	0.2
Vegetation segmentation (HSV)	0.2
Morphological processing	0.2
Feature extraction (ExG, texture, area)	0.1
Classification (Random Forest)	0.1
Visualization & output generation	0.1
Total per image	**0.9 seconds**

IX. VALIDATION AND LIMITATIONS

A. System Validation

Predicted vegetation health classifications were evaluated against manually observed ground conditions in the test images to assess the achieved performance of the proposed system.

Testing was accomplished with multiple park images under varying environmental conditions, with visual inspection used to validate the classification results of healthy, moderate and dry vegetation areas.

Table 4: Validation Results

Evaluation Category	Percentage
Correct classification	82%
Misclassification	18%

Overall system classification accuracy was found to be approximately 82%, demonstrating reliability for identifying vegetation health conditions. The majority of healthy vegetated areas were accurately classified however, similarities in visual features contributed to inaccuracies in classifying a small number of moderate/thinly vegetated areas due to the imbalance of the data set.

B. Limitations

Despite good performance, several limitations were observed during testing:

Table 5: System Limitations

Limitation	Description	Example
Lighting variations	Shadows and uneven lighting affect segmentation accuracy	Dark areas may appear as dry vegetation
Soil–vegetation similarity	Bare soil may have similar color to dry vegetation	Dry soil misclassified as vegetation
Mixed vegetation patches	Regions may contain both healthy and dry vegetation	Patch labeled as moderate instead of mixed
Small dataset size	Limited samples reduce model generalization	Fewer dry samples affect accuracy
Noise in segmentation	Imperfect masks affect feature extraction	Small false regions detected as vegetation

C. Specific Case Vegetation Condition Confusion

Compared to healthy vegetation, moderate and dry vegetation classes was more challenging for the model to separate due primarily to overlapping visual traits (reduced greenness, inconsistent textural characteristics, and partial dryness) being present in both classes.

The presence of overlapping characteristics, such as lower vegetation index (ExG) values and inconsistent texture patterns, led to situations where moderate patches of vegetation were incorrectly classified as dry, and vice versa. These factors decreased the amount of separation between the two classes, increasing the number of errors associated with their classification.

Both biological and environmental factors such as shade, bare ground, and mixed vegetation also contributed to greater confusion between these 2 classes.

By enhancing the dataset with more diverse representation of moderate and dry vegetation and adding more distinguishing features, there is a potential for decreasing misclassification and enhancing the overall model's performance.

X. CONCLUSION

In this paper, a Morphology Based Integrated Vegetation Health Monitoring System is presented using RGB images to assess vegetation condition. The proposed system consists of: Image Preprocessing Segmentation via HSV based color space segmentation Morphology transformations via morphological operations, such as erode, dilate, open, and close Feature extraction and, Classification via Random Forest Classification. The ultimate goal is to produce vegetation health map products and statistics.

Morphological operations, including Erosion, Dilation, Open, Close helped to significantly reduce noise, fill in removed areas (gaps), and provided an additional benefit of connecting discontiguous areas together, resulting in improved feature extraction and overall classification accuracy.

Experimental results indicated that the system provided an overall accuracy of ~82%, which indicates its reliability for classifying three classes (healthy, moderate, and dry). System accuracy was greatest for the healthy class, whereby the dry and moderate classifications were less accurate because of visual similarities between the two classifications, as well as limited training sample size for the classifications, causing confusion when classifying new classes.

The system is efficient with an average system processing time of ~0.9 seconds/image therefore providing a computationally efficient computational application that does not require GPU assistance. Therefore, this system is capable of being deployed in real-time and at a low cost, and allows the use of common computing equipment.

XI. FUTURE WORK

Future directions for this study's continuation will be as follows:

- Collect additional images of parks in various environments, including dry and mixed vegetation types, so that the data set can be expanded,
- Improve the accuracy of images by exploring advanced methods of segmentation for consideration of issues related to quality of light levels such as shadows, variable light conditions, etc., and to address differences in colour and texture between the soil and vegetation being represented in the images,
- Use new features to achieve better classification performance by adding new texture features from GLSM and new modified colour indices,
- To use deep learning methods for the extraction of quantitative measures from images by using techniques such as convolution neural networks (CNN) to automate the process of deriving and using quantitative features from images to improve the classification accuracy,

To enhance the use of drone or aerial imaging technology for large scale monitoring and mapping of parks or areas of agriculture.

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