ISSN PRINT 2319 1775 Online 2320 7876

Research paper **UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021**

Optimizing Air Quality Management with an Energy-Efficient Deep Learning Soft Sensor

Vijay Kumar Burugari, Koneru Lakshmaiah Education Foundation (KLEF), Vaddeswaram 522302, Andhra Pradesh, India

Abstract

This paper presents a novel approach for monitoring air quality by utilizing Cryptogams, a bio-indicator that can accurately reflect pollution levels. We introduce an advanced and energy-efficient deformable active contour model designed to track the growth of transplanted Cryptogams across various pollution sites. Our study focuses on monitoring the vegetative development of Cryptogams over a span of two weeks, showcasing the effectiveness of our proposed energy-efficient contour tracing model in precise tracking, resulting in more reliable pollution monitoring.

1. Introduction

Industrial and urban activities have severely impacted the environment, leading to pollution in air, water, land, and even space. Pollution monitoring has gained importance in both qualitative and quantitative contexts to understand and mitigate the detrimental effects of pollutants [1]. Various methods, such as mechanical sensors and chemical treatments, are used for monitoring pollution levels in the environment [2]. However, a more intriguing and effective approach involves the use of bio-indicators like Cryptogams, particularly lichens, which exhibit sensitivity to pollutants and can serve as natural biomonitoring tools. Cryptogams, with their unique symbiotic relationship between fungi and algae, absorb atmospheric pollutants and display physiological and morphological changes in response to varying pollution levels [3]. This paper explores the application of deep learning in image classification to analyze Cryptogam growth patterns, offering a novel method for pollution monitoring.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021

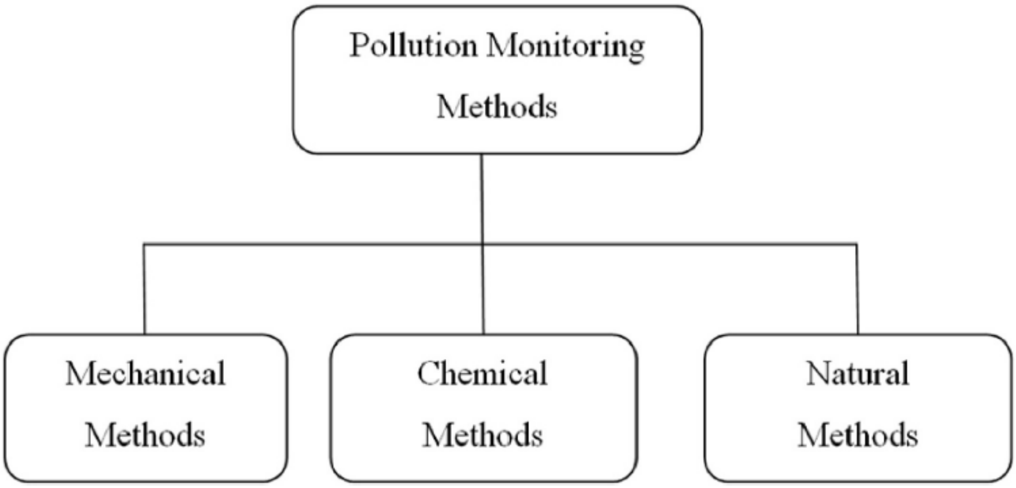

Fig. 1. Taxonomy of Pollution Monitoring methods.

Fig. 2. Common types of Cryptogams.

2. Literature survey

Cryptogam species are identified using various methods, including morphology, anatomy, and chemical profiling of the thallus. For environmental pollution monitoring, chemical profiling involves using tests like KOH, Calcium, and Potassium, followed by thin-layer chromatography to confirm Cryptogam compounds and species. Collecting wild Cryptogam samples is challenging, so noninvasive image processing techniques are used for identification. Machine learning techniques, such as pre-processing,

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021

boundary detection, feature selection, and classification, aid in image retrieval. Cryptogams have the advantage of surviving for extended periods, enabling monitoring at different stages and seasons. They can be used to calculate pollution levels without the need for a unique laboratory setup, unlike traditional methods that harm the species. Image enhancement and filtering techniques can improve image quality during processing. There are three levels of input in image processing: Low, Middle, and High levels. Urbanization and anthropo pressure have a direct impact on allantoin levels in Cryptogams, with Cadmium, Nickel, and Lead accumulation leading to increased allantoin levels. Nondestructive image processing techniques avoid damaging vegetation, unlike chemical examination. However, challenges exist in removing background substrate and learning the contour of Cryptogams due to their growth on various surfaces and shapes.

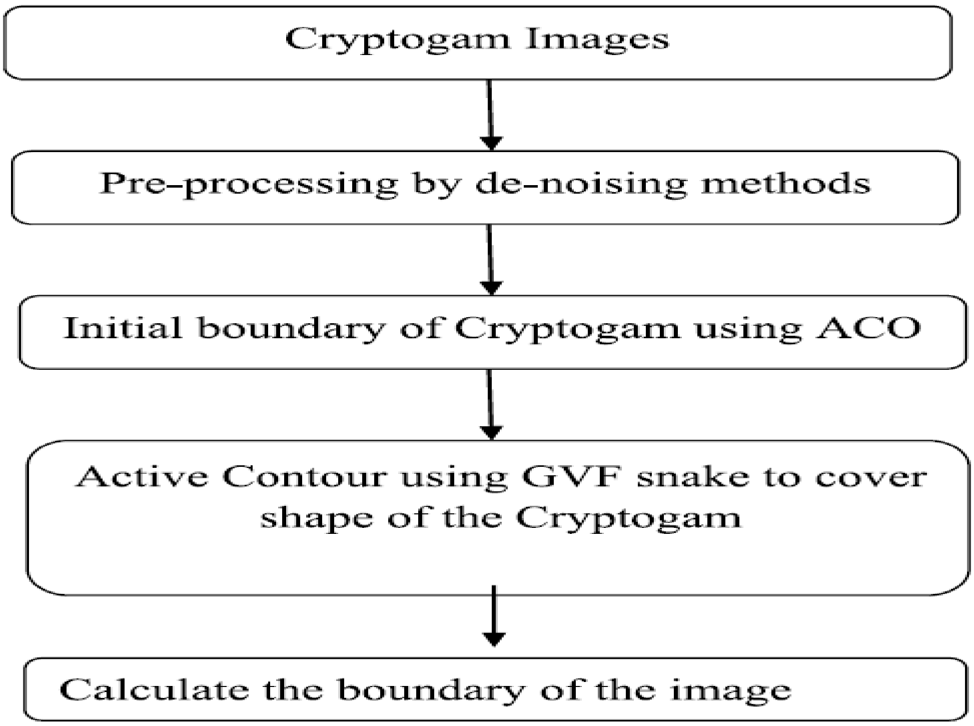

Fig. 3. Shape extraction process.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper **UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021**

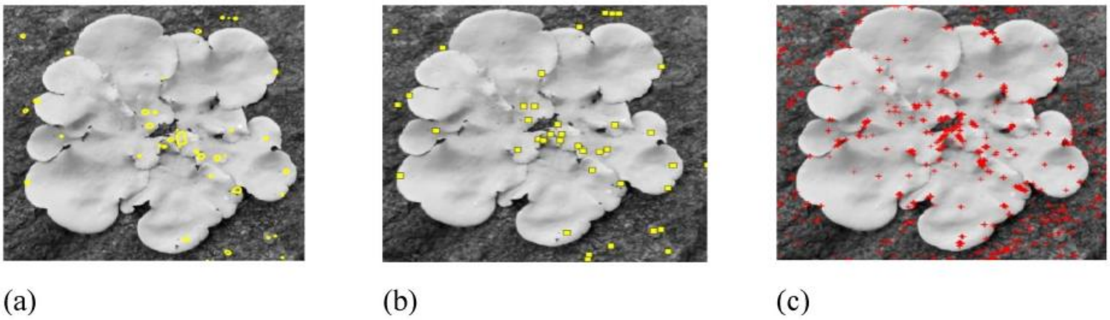

Fig. 4. Random dispatch of the ants (a) Sample image1 (b) Sample image2 (c) Sample image3.

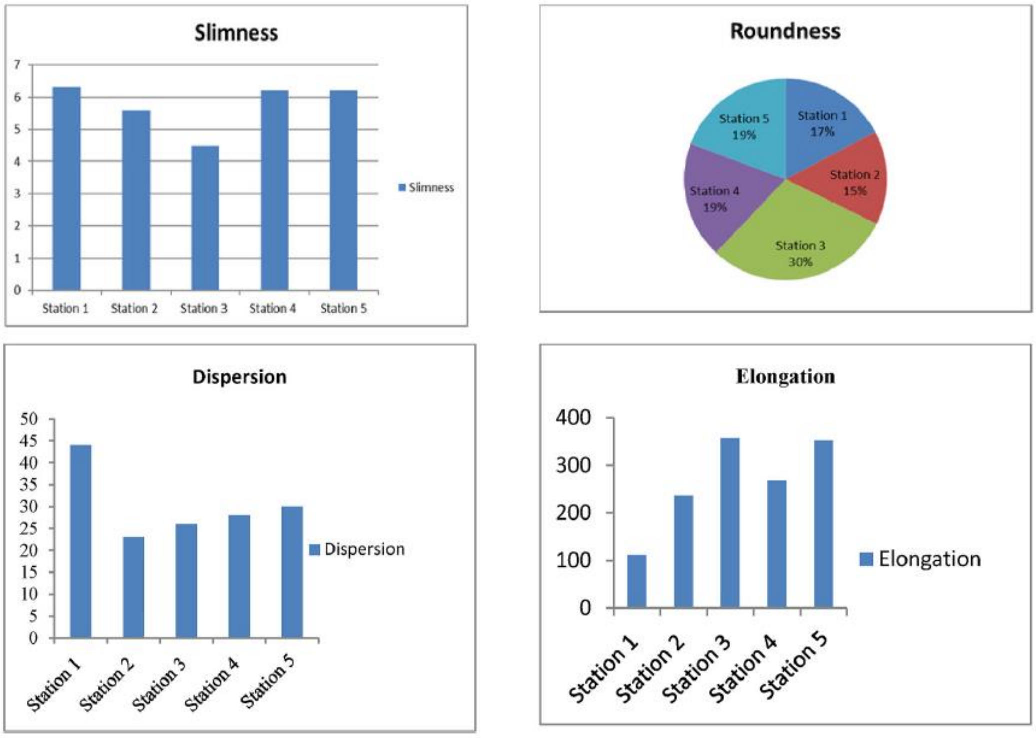

Fig. 5. Shape based features values extracted from the Cryptogam image using proposed method for the first week.

2.1. Cryptogam vegetation monitoring through ant colony optimization and gradient vector flow

The proposed methodology aims to measure the size of Cryptogam species to understand their growth levels under different climatic and imaging conditions. The complete workflow graph is shown in Fig. 3. The first step of the workflow involves preprocessing the Cryptogam images to achieve a low Mean Square Error (MSE) value, which is crucial for accurate analysis [17]. Noisy Cryptogam images are denoised during preprocessing, offering three advantages: noise reduction, management of irrelevant pixels, and enhancement of image quality. Next, the methodology focuses on detecting the edges and boundaries of the Cryptogam species. Since Cryptogams spread in an invariant manner on surfaces, delineating their boundaries can be challenging. To address this, an Enhanced Active Contour model is used to locate the boundary of the Cryptogam image while minimizing interference from other objects in the image. The initial boundary is determined using the Ant Colony algorithm, a bioinspired computing algorithm that finds the Region of Interest (ROI) in the image, which serves as a starting point for the active contour. Edge information is continuously updated for each iteration as an ant explores new points in the path. Subsequently, the output from the Enhanced Active Contour is used by the gradient vector flow model to obtain an optimized result for finding the shape features of the Cryptogam species. The gradient vector flow helps in understanding the structure and morphology of the Cryptogams. The overall objective of this methodology is to accurately measure the size and shape features of Cryptogam species under varying conditions, providing valuable insights into their growth patterns in different environments.

(a) **(b)** **(c)** **(d)** **(e)**

Fig. 8. (a) Resized image (b) Reduced background image (c) Masking Cryptogam ROI (d) Extracted Cryptogam image contour at iteration 500 (e) Exact boundary detection of Cryptogam image.

Table 1
Comparison of Accuracy index and processing time of proposed model with other state of art techniques.

Parameter	Edge Detection Technique	Visual attention combined with GVF	GVF snake algorithm	Proposed algorithm
Accuracy index	40.55%	92.12%	89.56%	91.45%
Process time (s)	55.37	6.46	9.56	5.56

Table 2
Cryptogam circumference due to pollution after transplantation.

Cryptogam growth (Days)	Station 1	Station 2	Station 3	Station 4	Station 5
1	55.8	49.2	36.4	62.6	60.6
3	45.6	39.6	35.6	75.2	63.2
5	36.2	32.1	39.1	87.7	67.4
7	28.6	20.5	38.5	100.1	86.1
10	15.35	10.9	39.9	112.4	98.4

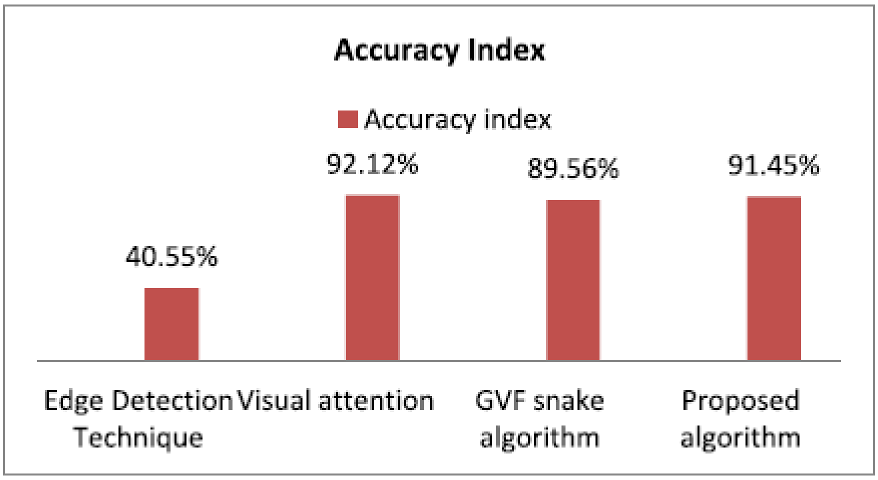

Fig. 9. Accuracy index.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021

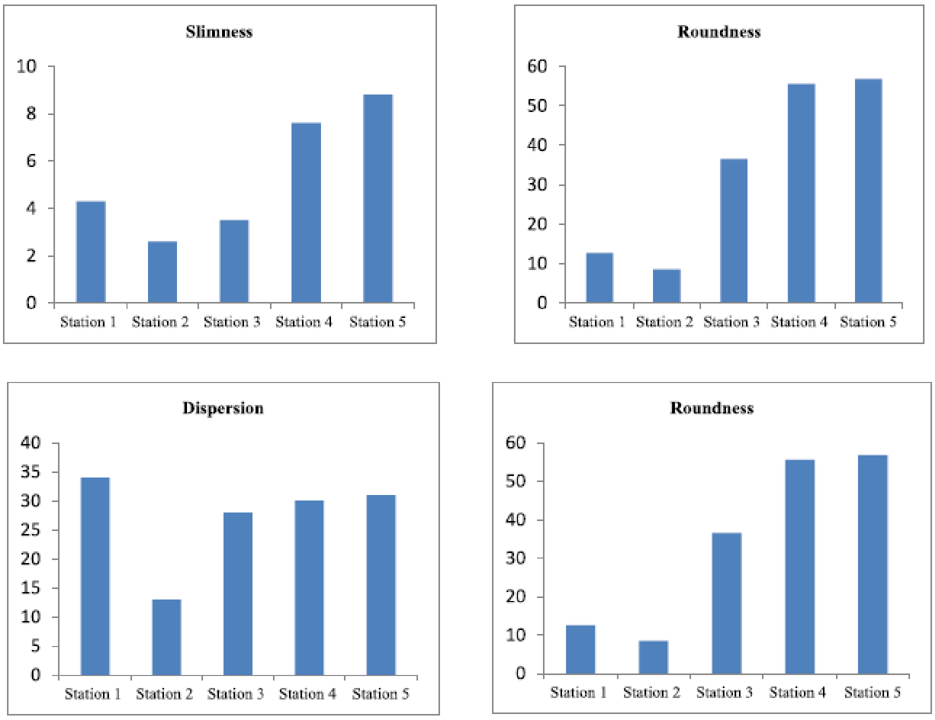

Fig. 6. Shape based features values extracted from the Cryptogam image using proposed method for second week station 1.

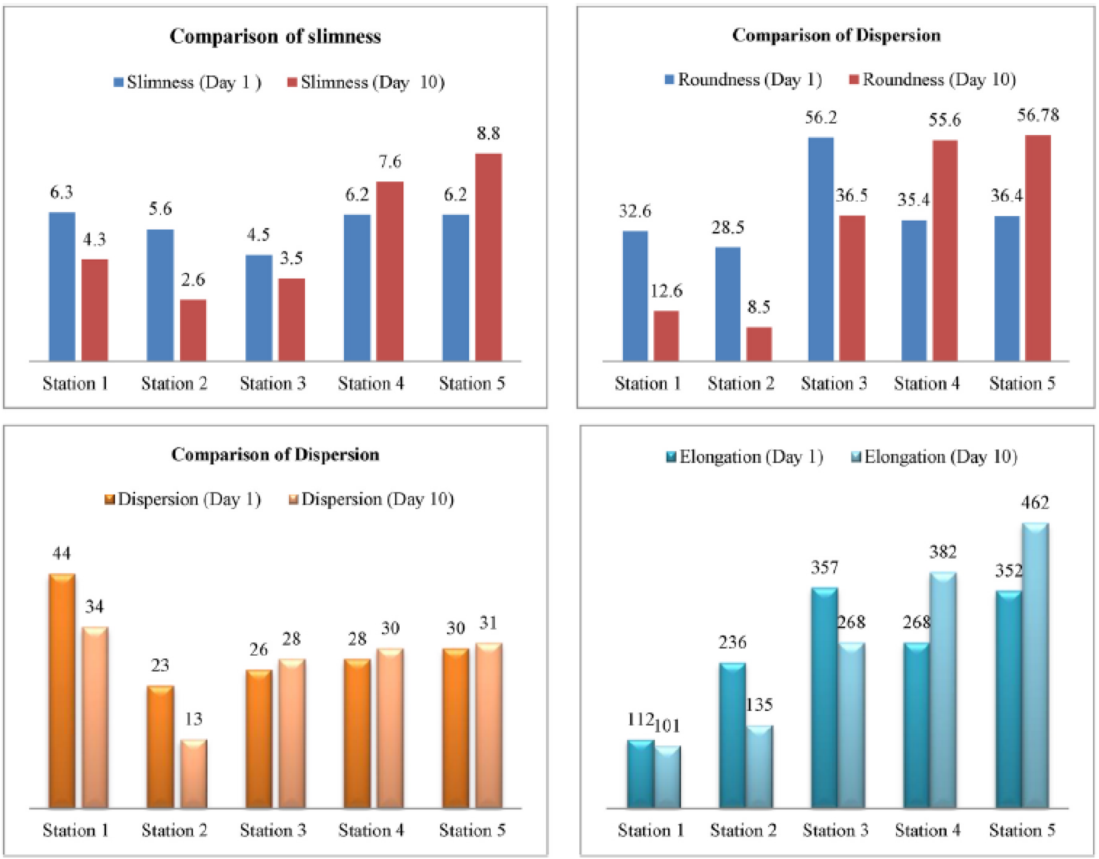

Fig. 7. Comparison of Shape based features values extracted from the Cryptogam image using proposed method for first and second week.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021

2.2. Transplantation of pollution sensitive cryptogam species and monitoring through focused image processing techniques

Parmotrema Tinctorum, a pollution sensitive species of Cryptogam which is sparingly found in highly industrialized south zone of India, is considered for this study. This species has large, loosely attached foliage thallus with distinctly broader lobes. Samples of the species are transplanted to monitor the transformation in change, color, texture and shape features in the context of pollution monitoring. This study was carried for an extensive period of 12 weeks at different sites. The Cryptogams were planted in extremely intense industrial areas in a highly polluted environment. The next genre, which experiences moderate levels of pollution. Cryptogams were also planted at multiple sites which have relatively lower pollution levels with a fresh atmosphere.

2.3. Preprocessing cryptogam images

Cryptogam images can have various backgrounds, and those captured from healthy forests often contain high-level data, especially at the edges of the picture. The accurate isolation of shapes and outlines is crucial for effective image processing techniques. However, non-uniform illumination in forest images can hinder the process of defining boundaries. Care must be taken during de-noising, as some de-noising methods may damage the original information. Therefore, pre-processing is essential to reduce noise in the image. The main goals of de-noising Cryptogam images are to remove speckle noise, impulsive noise, and smoothen the image. Speckle noise, in particular, can degrade image quality, affecting both size and colors [19,20].

2.4. Ant Colony Optimization (ACO) for contour detection

Table 3
Confusion matrix.

Confusion Matrix								
Algorithm	TP	TN	FP	FN	Accuracy	Precision	Recall	F-Measure
ACO	762	816	174	192	81.2	81.4	79.9	80.6
GVF	812	836	137	159	84.8	85.6	83.6	84.6
VGG16	906	915	54	69	93.1	94.4	92.9	93.6

ISSN PRINT 2319 1775 Online 2320 7876

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 10, Spl Iss 1, 2021

2.5. Enhanced deformable active contour model

Input: ParmotremaTinctorum image
Output:Extracted shape property of the Tinctorum image

Identify the source image
Initialize the shape property
Generate the PFT parameter matrix
For x=1: count
    For x=i: every iteration for shape
        $E_{snake} = E_{int}(L(s)) + E_{ext}(L(s))$ // energy calculation
      // Apply GVF snake equation for shape features
        $L(s)=[x(s), y(s)]$
 end
end

4. Conclusion and future works

The correlation between bio indicators and pollution levels is well-established, with the development of bio indicators serving as a valuable means to monitor pollution in specific regions. Cryptogams, in particular, are exemplary bio indicators, as their vegetative growth directly reflects pollution levels. To effectively monitor this growth, we employ advanced image processing techniques. This study introduces a novel and improved deformable active contour model, specifically designed for tracking Cryptogam growth from images of varying qualities. Our research delves into comprehensive discussions of preprocessing techniques and noise reduction mechanisms, enhancing the accuracy and reliability of our monitoring system.

References

[1] Cristina Fossi Maria, Ped`a Cristina, Montserrat Compa, Catherine Tsangaris, Carme Alomar, Francoise Claro, Christos Ioakeimidis, Francois Galgani, SaludDeudero TatjanaHema, Teresa Romeo, Pietro Battaglia, Andaloro Franco, IlariaCaliani, Silvia Casini, Cristina Panti, Matteo Baini, Bioindicators for monitoring marine litter ingestion and its impacts on Mediterranean biodiversity, Environ. Pollut. 237 (2018) 1023–1040.

[2] A. Akshay, Patil, K.S. Bhagat, Plants identification by leaf shape recognition: a review, Int. J. Eng. Trends Technol. 35 (2016) 675–688.

[3]Yadav, Y. P., & Tiwari, G. N. (1989). Demonstration plants of fibre reinforced plastic multiwick solar still: an experimental study. Solar & wind technology, 6(6), 653-666.