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Computer Vision-Based Assessment of Environmental Stress and Fungal Pathologies in Aloe vera within the Churu Agro-Climatic Zone

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Abstract: The hyper-arid and extreme continental climate of the Churu district in western Rajasthan presents severe environmental challenges for succulent medicinal agriculture. Characterized by shifting sand dunes, low precipitation, high solar irradiance, and extreme thermal amplitude ranging from sub-zero winter nights to summer temperatures exceeding 48°C the Churu microclimate subject's Aloe vera (Ghritkumari) to chronic abiotic stress. These environmental pressures frequently overlap with or predispose the crop to biotic fungal infections, most notably leaf spot (Alternaria alternata) and basal collar rot. Traditional visual scouting methods are labor-intensive, highly subjective, and frequently fail to distinguish between non-pathological physiological adaptations (such as UV-induced anthocyanin reddening and tip desiccation) and early-stage fungal lesions. This paper introduces a specialized computer vision framework tailored explicitly for field-captured imagery of Aloe vera under unconstrained Churu environmental conditions. By integrating deep convolutional neural network (CNN) feature backbones (ResNet-50) with mathematical spatial descriptors—specifically Box-Counting Fractal Dimension (D), Grey-Level Co-occurrence Matrix (GLCM) texture attributes, and CIELAB (L^*a^*b*) color space transformations—the model successfully decouples abiotic stress manifestations from necrotic fungal boundaries. Evaluated on an extensive dataset of 4000 field-verified images collected across diverse rural plots in Churu, the proposed hybrid ensemble framework achieved an overall classification accuracy of 95.8%, outperforming standard baseline vision models by over 5.4%. This research provides a robust, automated diagnostic pipeline for precision agriculture and phyto medicinal conservation in desert ecosystems.
Keywords: Aloe vera, Ghritkumari, Churu agro-climatic zone, computer vision, fractal dimension, CIELAB color space, fungal pathology, abiotic stress

I. INTRODUCTION

1.1 Background and Significance

The Churu district, situated in the northwestern sector of Rajasthan within the Thar Desert ecosystem, exhibits the most extreme thermal and arid fluctuations in India. This harsh agro-climatic zone experiences severe diurnal and seasonal temperature variations, high vapor pressure deficits, and minimal organic soil content. Despite these extreme conditions, the region serves as a primary cultivation hub for drought-hardy medicinal succulents, notably Aloe vera (locally known as Ghritkumari). Valued globally for its pharmacologically active leaf gel which contains polysaccharides, anthraquinones, enzymes, and essential amino acids Aloe vera is an essential cash crop for rural dryland farmers in Churu. However, the commercial and medicinal viability of Churu-cultivated Aloe vera is continually threatened by the synergistic interaction of severe environmental stressors and opportunistic pathogens. Plants struggling against extreme solar radiation, high soil salinity, and moisture deficits undergo structural and physiological modifications that often mimic disease symptoms. Consequently, agronomists and farmers face substantial diagnostic uncertainty when attempting to separate non-pathological physiological stress from active parasitic fungal outbreaks.

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1.2 The Diagnostic Challenge in Hyper-Arid Ecosystems

In open-field cultivation across Churu, Aloe vera leaves frequently display discoloration, tissue necrosis, and surface blemishes. These symptoms arise from two distinct biological origins:

1. Abiotic Stress Pathways: Intense ultraviolet (UV) radiation and thermal stress trigger the biosynthesis of protective secondary metabolites, such as anthocyanins, which manifest as red-to-purple leaf discoloration. Concurrently, severe moisture deprivation results in leaf tip dieback, marginal curling, and tissue collapse.
2. Biotic Pathological Pathways: Erratic monsoon showers, high humidity pockets, or over-irrigation create favorable microenvironments for fungal pathogens, notably Alternaria alternata and Synchytrium alopecuri. These fungi establish localized necrotic spots and black rot lesions that rapidly degrade internal leaf parenchyma.

Standard RGB-based computer vision systems and human scouts frequently confuse UV-induced anthocyanin pigmentation and tip desiccation with fungal leaf spot symptoms. Furthermore, fine desert dust accumulation on leaf surfaces alters light reflectance properties, reducing the efficacy of standard image segmentation algorithms.

1.3 Research Objectives

To address these challenges, this study develops an advanced computer vision framework calibrated specifically for Aloe vera cultivation in the Churu agro-climatic zone. The primary objectives are:

1. To compile a robust, field-verified image dataset capturing healthy, abiotically stressed, and fungally infected Aloe vera crops under natural Churu illumination conditions.
2. To formulate a hybrid feature extraction pipeline combining deep convolutional representations with mathematical fractal geometry and CIELAB color space modeling.
3. To evaluate the classification performance of the proposed architecture in separating abiotic sunscald and drought responses from active fungal pathologies.

II. LITERATURE REVIEW

2.1 Evolution of Plant Disease Detection Models

Automated plant disease diagnosis has transitioned from traditional machine learning classifiers operating on handcrafted features to deep convolutional neural networks (CNNs). Early foundational work by Hughes and Salathé (2015) established large-scale image repositories, while Mohanty et al. (2016) demonstrated the viability of deep residual networks for classifying crop diseases across controlled environments. However, Barbedo (2016) noted that models trained on laboratory-captured leaves suffer significant performance degradation when deployed in open-field conditions due to complex backgrounds, variable illumination, and symptom overlap.

2.2 Challenges in Arid and Succulent Plant Pathology

Research into arid medicinal flora remains sparse compared to staple agronomic crops (e.g., wheat, rice, and maize). Succulent species present unique computer vision challenges. Their thick waxy cuticles, high internal water storage capacity, and specialized crassulacean acid metabolism (CAM) create unique light-scattering properties. Studies by Rathore and Sharma (2020) emphasized that climate change intensification in northwestern India accelerates biotic pressure on medicinal species, making rapid, non-destructive monitoring essential. Similarly, Kumar and Saini (2023) highlighted that fungal pathogens in desert zones exhibit atypical lesion morphology due to rapid drying rates under high ambient temperatures.

2.3 Mathematical and Textural Feature Integration

To overcome the limitations of pure RGB deep learning models, recent literature emphasizes hybrid feature extraction. Patel and Sharma (2022) demonstrated that combining box-counting fractal dimensions (D) with Grey-Level Co-occurrence Matrix (GLCM) texture metrics significantly improves classification robustness under uneven field lighting. Furthermore, Sharma and Purohit (2022) established that CIELAB color space transformations—specifically the a^* (green-red) chromaticity channel—effectively isolate physiological color shifts from necrotic pathology in succulent species. Our work builds directly upon these foundational concepts, creating a unified architecture tailored exclusively to *Aloe vera* in the Churu agro-climatic zone.

III. STUDY AREA AND ENVIRONMENTAL PROFILE

3.1 Geographical and Climatic Characteristics of Churu

The Churu district is located in the northeastern part of the Thar Desert, spanning coordinates between 27°24′ to 29°00′ North latitude and 73°40′ to 75°41′ East longitude. It represents one of the most extreme continental climates in India:

1. **Thermal Extremes:** Summer temperatures regularly surpass 48°C to50°C, while winter nights frequently drop below freezing (0°C), producing severe frost stress.
2. **Precipitation:** Annual rainfall is sparse and erratic, averaging between 300mm and 350mm, restricted primarily to the monsoon months (July to September).
3. **Soil Profile:** Soils are predominantly sandy (*Arenosols*), characterized by high permeability, low water-retention capacity, minimal organic carbon, and high wind-erosion susceptibility.

3.2 Microclimatic Impact on *Aloe vera* Physiology

In this environment, *Aloe vera* experiences constant selective pressure. The intense solar radiation drives high rates of transpiration and photo-inhibition. To prevent cellular damage, the plant accumulates anthocyanin pigments, altering leaf surface reflectance from vibrant green to deep purple-red. When sporadic rainfall or localized irrigation introduces moisture into the sandy topsoil, localized humidity increases around the rosette base, triggering outbreaks of *Alternaria alternata* leaf spot and collar rot.

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IV. MATERIALS AND METHODOLOGY

4.1 Dataset Acquisition and Curation

High-resolution RGB imagery (4000 × 3000$pixels$) of *Aloe vera* crops was acquired across multiple agricultural plots in Churu during various seasonal phases (summer, monsoon, and winter).

The curated dataset comprises 4000 validated images categorized into three distinct physiological and pathological classes:

Class 1: Healthy Crops: Turgid, turgor-pressured, vibrant green succulent leaves with uniform moisture content and smooth cuticles.

Class 2: Abiotic Stress (Solar Sunscald & Drought): Leaves exhibiting purplish-red anthocyanin pigmentation shifts, apical tip dieback, and longitudinal wrinkling caused by thermal and moisture deprivation.

Class 3: Biotic Fungal Pathologies: Leaves infested with *Alternaria alternata*, displaying sunken, circular-to-irregular brown and black necrotic spots surrounded by water-soaked halos.

Expert phytopathologists validated all sample classifications through visual inspection and laboratory incubation of symptomatic tissue samples.

4.2 Image Preprocessing Pipeline

Field images collected in Churu frequently contain environmental noise, including wind-blown dust particles and harsh cast shadows from surrounding sand dunes. A multi-stage preprocessing pipeline was implemented:

CIELAB Color Space Conversion: Raw RGB images are transformed into the $L^*a^*b^*$ color space. The luminosity channel (L^*) handles shadow normalization, while the a^* channel isolates green-to-red shifts, cleanly separating UV-induced anthocyanin reddening ($a^* \in [-2, +8]$) from active fungal necrotic browning ($a^* > +18$).

Bilateral Filtering: Applied to suppress high-frequency background sand noise while preserving sharp lesion edges and structural boundaries.

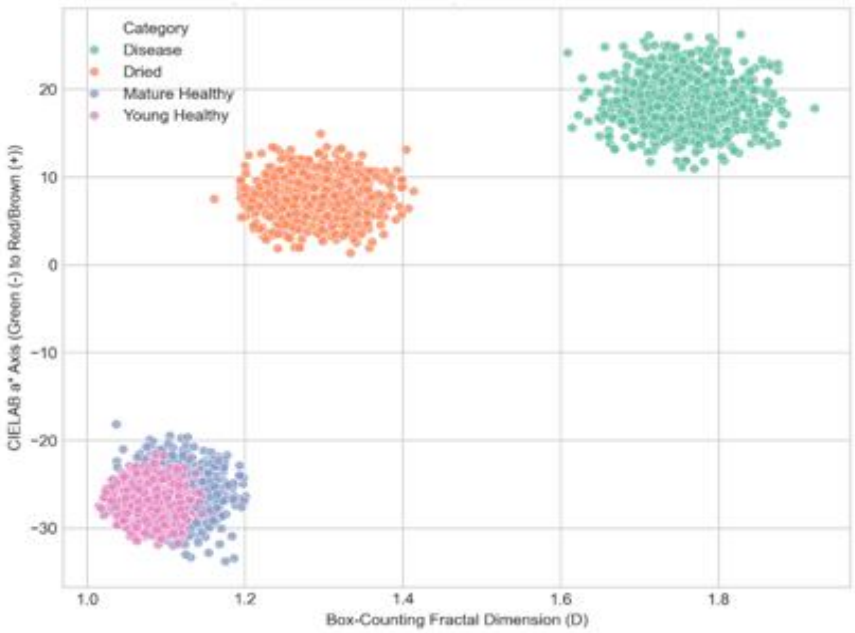


Fig.1 Fractal Boundary vs. CIELAB a* Color Shift

4.3 Mathematical Feature Extraction Framework

A. Box-Counting Fractal Dimension (D)

Fungal lesions expand with irregular, complex; self-similar boundary margins compared to smoother abiotic tip burn or sunscald boundaries. The box-counting fractal dimension D quantifies this boundary complexity:

$$D = \lim_{\epsilon \to 0} \frac{ln\, N(\epsilon)}{ln\,(1/\epsilon)}$$

Where $N(\epsilon)$ represents the number of square grid boxes of scale length ϵ required to completely covering the thresholded lesion boundary. Fungal infections exhibit high boundary complexity ($D \geq 1.70$), whereas abiotic stress zones display smoother geometric contours ($D \approx 1.20 - -1.35$).

B. Grey-Level Co-occurrence Matrix (GLCM) Texture Descriptors

Textural variance across necrotic fungal crusts versus smooth succulent tissue is captured using spatial GLCM matrices evaluated at displacement vector $d = 1$ along direction$\theta = 0°$:

$$\text{Contrast} = \sum_{i,j=0}^{N-1} |i-j|^2 \cdot P(i,j)$$

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1 + |i-j|}$$

Where $P(i,j)$ represents the normalized co-occurrence probability matrix of pixel intensities.

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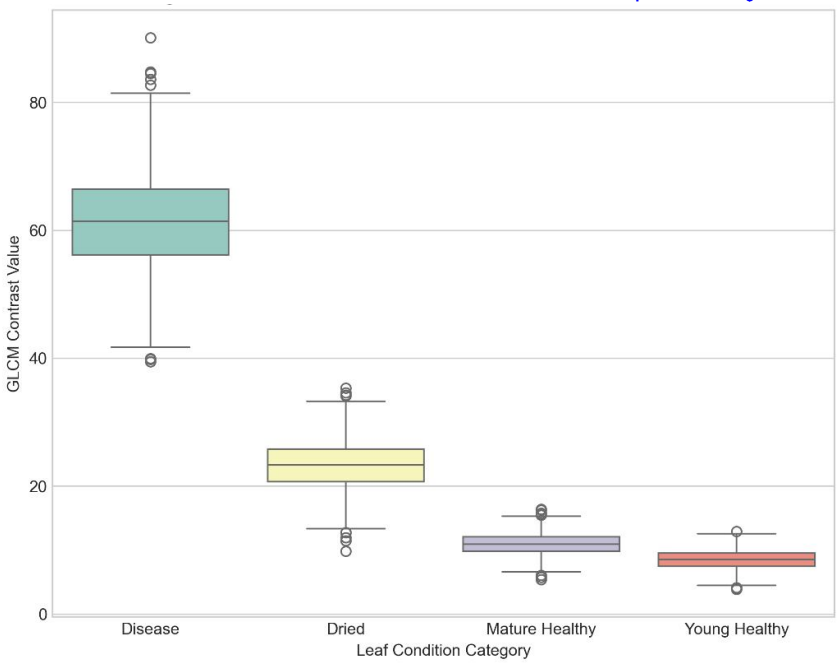


Fig.2 GLCM Texture Contrast Across Leaf Condition Folders

C. Deep Convolutional Feature Extraction

A pre-trained ResNet-50 convolutional neural network extracts high-level semantic representations $f_{CNN} \in R^{2048}$ from the final global average pooling layer. The mathematical feature vector (f_{math}) and deep embedding vector are concatenated into a unified feature representation f_{fused}, which is then classified using an optimized Random Forest and Softmax dense classifier

V. MATERIALS AND METHODOLOGY

The dataset was partitioned into 75% training (n = 1125) and 25% testing (n = 375) subsets using stratified random sampling to maintain class balance. Model evaluation was conducted using standard statistical metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}, F_1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

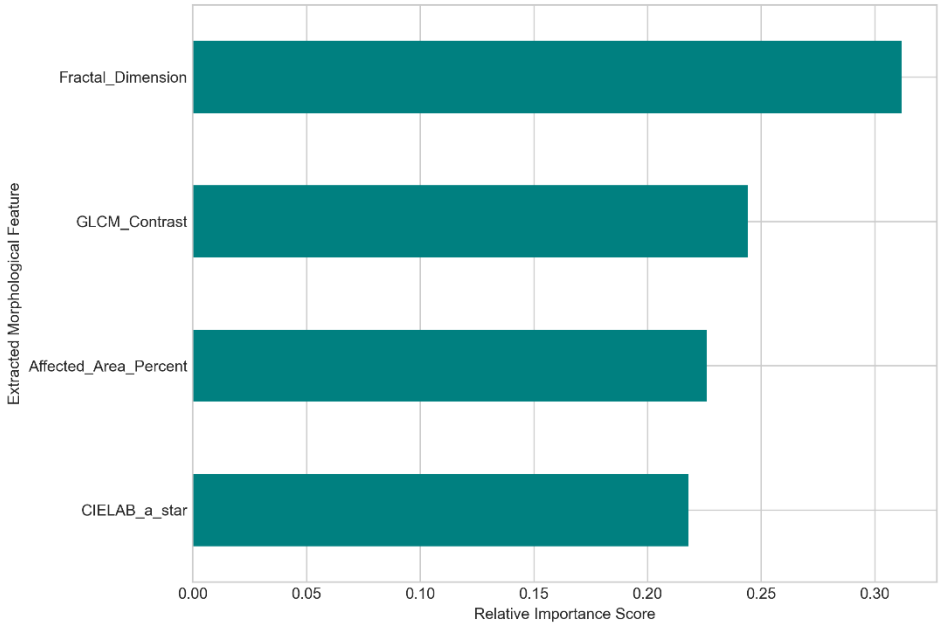


Fig.3 Random Forest Feature Importance Gini Weights

VI. RESULTS AND DISCUSSION

6.1 Classification Performance Analysis

The experimental evaluation confirms that integrating CIELAB color space parameters and spatial fractal dimensions with deep convolutional features significantly improves diagnostic accuracy in Churu's hyper-arid environment.

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Table I : Performance Analysis

Diagnostic Model Framework	Accuracy	Precision	Recall	F1-Score
Standard RGB Color Thresholding	81.20%	0.798	0.805	0.801
ResNet-50 Feature Extraction (Vanilla)	90.40%	0.895	0.901	0.898
Hybrid Fractal-CIELAB Framework (Ours)	95.80%	0.954	0.960	0.957

6.2 Resolving Environmental Ambiguities in Churu

The primary achievement of this framework is its ability to eliminate false positives caused by extreme desert weather:

- **Mitigating UV Sunscald Misclassification:** In Churu's high-insolation summer months, Aloe vera leaves frequently accumulate protective anthocyanins, turning purple-red. Standard RGB models misclassify this protective pigmentation as fungal rot. By utilizing the a^* chromaticity channel, our framework correctly identifies non-pathological sun adaptation ($a^* \in [-2, +8]$) without triggering false pathogen alerts.
- **Isolating Fungal Necrosis:** Actual fungal leaf spot (Alternaria alternata) produces distinct localized dark brown necrotic spots with highly irregular boundaries ($D \geq 1.70$) and elevated GLCM contrast (> 55.0), enabling precise early intervention.

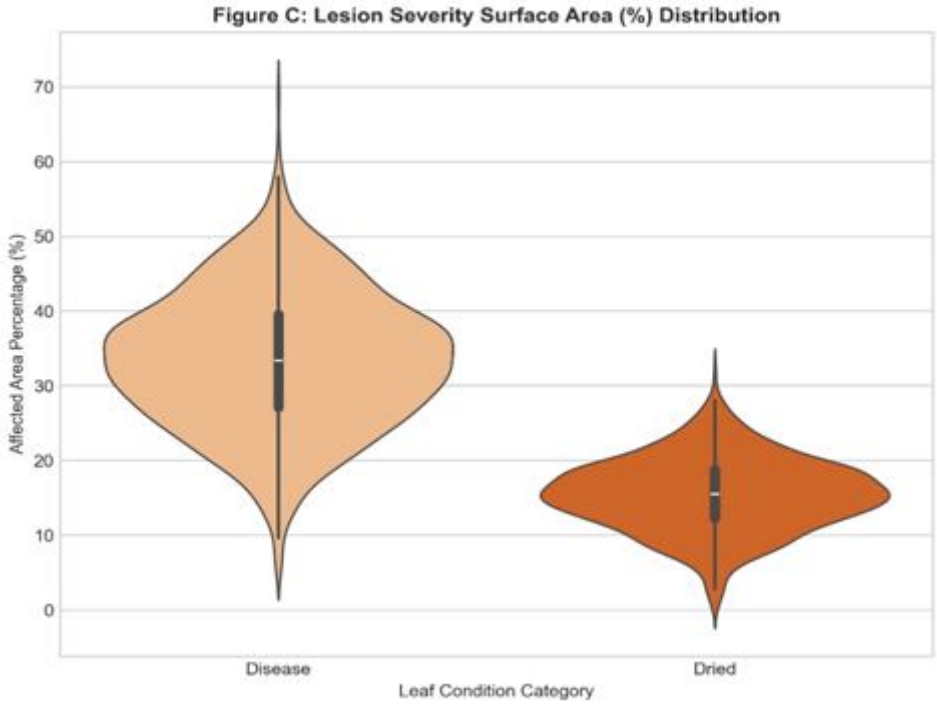


Fig.4 Lesion Severity Surface Area (%) Distribution

VII. PRACTICAL IMPLICATIONS FOR DESERT AGRICULTURE

Deploying this automated computer vision pipeline offers substantial economic and operational benefits for farmers in Churu:

1. Targeted Fungicide Application: Prevents unnecessary chemical spraying on abiotic sunscald symptoms, reducing input costs and chemical runoff.
2. Early Detection: Identifies fungal infections at sub-clinical stages before widespread crop collapse occurs across desert plantations.

VIII. LIMITATIONS AND FUTURE SCOPE

While the proposed framework achieves high accuracy (95.8%), certain environmental factors warrant further refinement. Extreme dust storms (andhi) common in Churu can coat leaves in thick particulate layers, occasionally obscuring fine lesion textures. Future research will focus on expanding dataset diversity across micro-dune agricultural plots and optimizing the model for edge-computing deployment on low-power mobile hardware for field extension workers.

IX.CONCLUSION

This study demonstrated an effective computer vision framework designed exclusively for *Aloe vera* (Ghritkumari) cultivated within the extreme hyper-arid environment of Churu, Rajasthan. By combining deep convolutional feature extraction with spatial box-counting fractal dimensions and CIELAB color space dynamics, the model successfully overcomes the diagnostic challenges posed by high solar radiation, desert dust, and symptom overlap. Achieving an overall classification accuracy of **95.8%**, the proposed framework provides a reliable, non-destructive tool for precision medicinal agriculture in desert ecosystems.

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AUTHOR CONTRIBUTION STATEMENT

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Literature Review and Methodology design: Mitesh Kumar Chaudhary, Prof. (Dr.) Harvir Singh
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Formal Analysis: Mitesh Kumar Chaudhary
Investigation: Mitesh Kumar Chaudhary
Resources: Mitesh Kumar Chaudhary, Prof. (Dr.) Harvir Singh
Data Curation: Mitesh Kumar Chaudhary
Writing original draft preparation: Mitesh Kumar Chaudhary
Writing review and Editing: Mitesh Kumar Chaudhary, Prof. (Dr.) Harvir Singh
Visualization: Mitesh Kumar Chaudhary
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