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## Advances in Geospatial Technology for Early Detection of Mango Leaf Diseases

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### Abstract

Mango leaves are susceptible to pests and pathogens including anthracnose, powdery mildew, diebacks, bacterial infection which cause serious loss of mango production, quality and sustainability. Recent developments in geospatial technology have provided new opportunities for the early, accurate, and large-scale detection of disease. This article offers a comprehensive review of methods, datasets and tools for monitoring mango leaf diseases through remote sensing and geoscience. High-resolution UAV images, multispectral and hyperspectral satellite data (e.g. Sentinel-3) along with field level spectral information serve as the basic sources of data for disease detection. There is a need for preprocessing steps such as resizing, denoising and normalization to enhance the reliability of models. The feature extraction with the help of vegetation indices, Band Ratios and texture metric GLCM increases the discrimination capacity between healthy and infected leaf. SVM, Random Forest, CNNs, and hybrid models of machine learning and deep learning have demonstrated high performance in classification when trained on a well-processed dataset. A key advance presented in this review is the development of portable spectrometers, which provide very accurate leaf-level reflectance profiles and become the crucial ground truth for calibrating geospatial disease detection models. The combined use of spectrometer data with UAV and satellite imagery significantly enhances disease identification sensitivity, especially at early stages of disease infection when the visual symptoms are minimal. In general, this review confirms that combining geospatial technologies, spectroscopy, and smart classification frameworks will provide an efficient, accurate, and scalable solution for mango disease monitoring to support precision horticulture and sustainable orchard management.

### Introduction

Mango is one of the most important tropical fruit crops grown in Asia, Africa and Latin America but India is largest producer in the world. It is well-adapted, economically valuable, and culturally significant, and forms a central component of horticulture systems [1]. The leaf development is essential to photosynthesis; nutrients transport and all other tree vigor at direct effect on fruit

yield and quality. But, mango orchards are also commonly subject to several biological stresses such as foliar diseases which severely reduce productivity in the absence of identification and management in time. This may come as a consequence of anthracnose, powdery mildew, and bacterial leaf spot disease, which frequently cause premature leaf drop, reduced canopy photosynthetic capacity and production loss.

This disease is critical to early diagnosis since disease progression quickly takes place under favorable environmental conditions, such as high humidity or temperature fluctuations [2][3]. Earlier diagnosis enables farmers to focus the targeted intervention, reduce pesticide abuse, mitigate economic loss and allow for improved orchard health. The sooner your farming has been tracked, the better it can be maintained with the help of early monitoring that will reduce the overuse of chemical compounds and prevent disease outbreaks at local scales [4].

The method of disease detection is usually manual field inspection by experts, visual assessment of symptoms, and laboratory-based diagnostics. These methods are subjective, time consuming and often impossible for large orchards. Visual diagnosis is sometimes false when symptoms are minimal or hidden at the canopy [5]. Even the traditional approach for precision agriculture is inefficient due to an inherent lack of experienced expertise, high labor cost and delayed response time. These limitations illustrate the need for more flexible, rapid, objective methods of disease surveillance

in larger spatial scales [6]. Global technologies such as Remote Sensing (RS), Geographic Information Systems (GIS), and Unmanned Aerial Vehicles (UAVs) have evolved as powerful means of assessing crop health. These technologies allow analysis of physiological and biochemical changes in leaves before they appear to be seen as the result of visible symptoms [7]. Multispectral, hyperspectral, and thermal sensors can measure reflectance patterns associated with chlorophyll content, humidity stress, pigment degradation, and disease-induced canopy changes. GIS can help to analyze disease hotspots and identify diseases, providing insight into disease distribution and spread. In conjunction, geospatial data provide a non-destructive, cost-effective and high-frequency monitoring that can cover large mango farms [8]. This review aims to restructure existing literature on the detection of mango leaf disease as depicted in Fig.1 with geospatial technology, and examine alternatives to remote sensing software for measuring the impact of different remote sensing platforms, vegetation indices, and machine learning methods.



*Figure 1. Mango leaf with healthy plant and disease plant*

This review presents the role of satellites, UAVs, and proximal sensors in disease surveillance, discusses image processing and classification strategies, and reviews its strengths and weaknesses. Through analyzing global and regional studies, this review describes missing knowledge and proposes next steps to improve early disease detection, large scale mapping and precision orchard management. It focuses on spectral behavior analysis, vegetation index performance, AI-based detection and the incorporation of geospatial data for complete disease monitoring. This follows by literature

review as well as general methods for disease detection followed by results analysis followed by conclusion.

### **Literature Review**

In this section, we review and synthesize existing literature on mango leaf disease detection, geospatial methods, and related remote-sensing techniques. We organize the review around disease detection via image processing and machine learning, geospatial and remote sensing applications in mango monitoring, and disease

detection via ASD Spectrometer. Also, highlighted gaps and challenges in the literature. The paper focuses on mango leaf disease detection primarily through image processing techniques. It emphasizes the importance of accurately diagnosing diseases like Anthracnose, Powdery Mildew, and Sooty Mold using image preprocessing, segmentation, feature extraction like leaf characteristics, such as their main and minor axes, are acquired during this phase, and various classification methods are then applied to diagnose the illness based on the extracted features [9]. Another author combine convolutional kernels and self-attention (transformer-style) to build the ViX-MangoEFormer architecture in which they have used large dataset (25,530 images), they achieve extremely high performance F1 score = 99.78% and MCC = 99.34%. They also use explainable AI techniques to produce pixel-level explanations, making the decision process transparent and more trustworthy [10].

Another collected UAV multispectral imagery over a large mango orchard for 65 acres and generated high-resolution orthomosaics. They used the YOLOv7 object detection framework to detect individual mango trees, followed by precise canopy segmentation using the Segment Anything Model (SAM) by achieving excellent agreement with ground truth ( $R \approx 0.97$ ) [11]. One of the author used Landsat 7 and 8 satellite imagery and derived vegetation indices like EVI, GNDVI, NDVI, and LSWI. VIs with weather variables (rainfall, temperature, evapotranspiration, solar radiation, VPD), they developed a model to forecast mango yield over multiple years. Though not directly disease detection, this study shows how remote sensing and time-series analysis can be used to monitor canopy health and productivity, which could correlate with disease stress in future work [12]. Another author used airborne or proximal hyperspectral data (VNIR) and applied chemometric machine-learning methods (PLSR, PCR, SVR). Their models PLSR combined with SVR or Cubist delivered high accuracy for nutrient prediction, especially when combining linear and non-linear modeling techniques [13]. Authors [14] used spectroradiometer to evaluate the evolution of anthracnose in mango fruits. Three stages of development in the mango were analyzed (healthy, asymptomatic and diseased) and the performance was evaluated with support vector machines (SVM) and random forest (RF). The principal component analysis (PCA) and linear discriminant analysis (LDA) were used to reduce the dimensionality and identify the most significant bands of the spectrum used, with the help of a Gaussian filter. A total of 61 significant

bands with PCA and 29 significant bands with LDA were found. The best evaluation performance was obtained with LDA reaching an accuracy of 91–100% in the three classes. There is a clear research gap in integrating leaf-level disease models with spatial remote-sensing for orchard-scale disease surveillance. Also, mango-specific indices for disease, and models capable of distinguishing disease from abiotic stress, remain underexplored. Future research must address these gaps by creating disease-sensitive spectral indices, scaling disease detection from leaves to orchards, and ensuring models are interpretable and field-deployable.

### Methodology

The methodology for mango leaf disease detection using geospatial technology typically begins with the acquisition of appropriate datasets, followed by systematic pre-processing, data augmentation, feature extraction, model training, and evaluation. Figure 2 shows diagrammatic representation of proposed methodology.

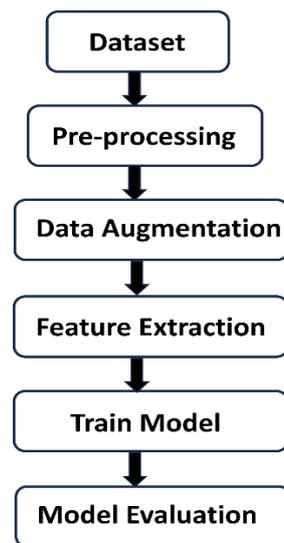


Figure 2. Proposed Methodology

### Dataset

Dataset acquisition serves as the basis for the whole process since the spatial, spectral, and temporal quality of the input data greatly affects how accurately illnesses are detected. Most research use three main classes of datasets: UAV-based imaging, satellite-based imaging, and controlled leaf-level image collections. While giving flexibility for on-demand and multi-angle imaging of mango plantations, UAV photography provides sub-centimeter resolution that allows fine-scale disease signs like anthracnose sores or powdery mildew patches to be seen. Using spectral changes linked with chlorosis, necrosis,

pigment loss, and other stress indicators, orchard-scale disease mapping is enabled by satellite datasets including Sentinel-2, Landsat-8/9, and high-resolution commercial imagery. Controlled, leaf-level datasets recorded using digital cameras or mobile phones are also utilized by many researchers mostly for benchmarking deep learning models and extracting disease-specific texture and color features. Every dataset could also include metadata describing sensor properties, acquisition circumstances, location, or disease categories [15][16].

### Pre-processing

Pre-processing turns into a vital phase after the dataset has been compiled to guarantee images are cleaned, standardized, and ready for feature extraction or deep learning algorithms [17]. Normally, images taken from field situations suffer from changes in noise, size, lighting, and orientation. Resizing is done to fix all input images to a constant dimension—usually 224x224 or 256x256 pixels—thereby enabling them to be compatible with conventional machine learning or deep learning frameworks, so tackling these inconsistencies [18]. While retaining important disease-related textures, noise reduction methods like Gaussian, median, or bilateral filtering are utilized to reduce sensor noise, atmospheric disturbances, and illumination-caused variance [19]. Spectral noise is usually corrected for multispectral and hyperspectral data using Savitzky–Golay filtering to preserve smooth spectral curves. Normalizing helps to lessen variations in contrast and brightness between images. While reflectance normalization is used on spectral datasets to harmonize radiometric values, techniques like min-max normalization or z-score standardization help to steady the learning process by guaranteeing uniform intensity distributions [20].

### Data Augmentation

Data augmentation approaches are used to improve model generalization and so increase dataset diversity even further. Addressing class inequality and improving model robustness against environmental changes depend mostly on augmentation. Common UAV or ground-based imagery viewing distances and angles are reproduced by geometrical transformations including rotation, flipping, scaling, and zooming [21]. Photometric corrections imitating variations brought on by cloud cover, light intensity, or camera exposure discrepancies include brightness and contrast tweaking or color jittering. Adding artificial noise like

Gaussian or speckle noise equips the model to deal with flaws in actual photos resulting from hardware restrictions or atmospheric phenomena. By increasing the training data and lowering overfitting risk, augmentation improves the model's capacity to adjust to unexpected orchard situations [22].

### Feature Extraction

Particularly for conventional machine learning techniques, feature extraction marks an important stage in the pipeline. Often used to extract statistical descriptors like contrast, homogeneity, correlation, and entropy—which describe disease-induced changes in leaf texture—are texture-based approaches such the Gray Level Co-occurrence Matrix (GLCM) [23]. Likewise employed to measure micro-textural patterns related to fungal spots, blighting patches, and mildew formations are local binary patterns (LBP). Distinguish patterns of discoloration caused by nutrient shortages or pathogen attacks with the aid of color features retrieved from RGB or HSV color spaces as well as vegetation indices such Excess Green (ExG) or Excess Red (ExR). Early disease detection depends greatly on spectral features derived from visible, red-edge, near-infrared, and short-wave infrared bands while utilizing geospatial data as spectral reflectance often reveals physiological stress before observable symptoms show. Common spectral feature analysis indexes are NDVI, GNDVI, Red-Edge NDVI, PRI, and chlorophyll indicators (CIgreen, CIred-edge). Deep learning algorithms automatically learn hierarchical representations—from simple edges and textures to sophisticated disease-specific structures—therefore handcrafted features are not needed [24].

### Train Model

After feature extraction, machine learning and deep learning models are taught to categorize healthy and ill leaves or to gauge the degree of infection. When manually created features act as input, traditional machine learning techniques including Support Vector Machines (SVM), Random Forests, K-Nearest Neighbors (KNN), Decision Trees, and Gradient Boosting classifiers are much used. These models are quite light and need little computing power; they are excellent in situations including organized spectral or texture traits. Conversely, deep learning methods use convolutional neural networks (CNNs) or sophisticated architectures including ResNet, VGG, DenseNet, MobileNet, and EfficientNet to extract traits straight from raw images. Since it uses pre-trained weights from extensive image databases to increase classification accuracy and

save training time, transfer learning is especially well-known in mango disease research. Some investigations additionally employ hybrid techniques whereby CNN is combined with SVM for better decision boundaries or CNN-LSTM combos for spatio-temporal UAV or satellite imaging analysis. Back-propagation, optimization using Adam or stochastic gradient descent, and regularization approaches like dropout and batch normalization are all usual elements of model training that help to avoid overfitting [25][26].

### Model Evaluation

Model evaluation, the final stage in the approach, uses statistical and geospatial indicators to assess trained classifier performance. The model's ability to appropriately distinguish between each disease class is measured using categorization measures including accuracy, precision, recall, F1-score, and Cohen's kappa coefficient. Misclassification patterns and class-wise performance are revealed by confusion matrices. Regression metrics like RMSE, MAE, and  $R^2$  are frequently used when the goal is to forecast illness severity or biophysical characteristics. Spatial validation is as important in geospatial applications, where it entails comparing expected disease patterns with field observations, disease incidence maps, or orchard-level assessments based on UAV or satellite data. These several assessment methods guarantee that the created models are strong, dependable, and appropriate for real-world mango disease monitoring and management [27].

### Result Analysis

Together, the examined studies show that mango leaf disease detection has been greatly improved in accuracy and efficiency by geospatial technologies in conjunction with deep learning and machine learning systems. Findings from several studies show that high-resolution UAV imagery and spectral data from satellite can detect both early-stage physiological stress and visible illness symptoms with complementary strengths. Because of their fine spatial granularity, drone-based RGB and multispectral pictures consistently provided better detection performance, so enabling CNN models to exactly learn lesion patterns and texture variations linked with anthracnose, powdery mildew, sooty mold, and nutrient shortages. Using deep CNNs such as ResNet50, EfficientNet, and VGG16 on UAV-collected data, several research, for instance, showed categorization accuracies over 95%, hence underlining the great capacity of deep learning for extracting discriminative

disease characteristics. Conversely, less strong in feature learning conventional machine learning methods such SVM, Random Forest, and Gradient Boosting displayed excellent performance when textural features (GLCM, LBP), color histograms, and spectral indexes were well designed. Usually attaining 85 to 92% in accuracy, these models showed their usefulness in situations with few data or little resources.

Studies show a clear trend whereby data augmentation and pre-processing greatly affect model stability and generalizing. Because augmentation accounted for illumination changes, leaf rotations, and noise in UAV photographs, models trained on enhanced datasets in field settings generated more dependable predictions. Particularly in hyperspectral and multispectral workflows where spectral smoothing enhanced the dependability of vegetation indices connected to illness progression, normalization and noise reduction were also very important. Studies using satellite data revealed that NIR and red-edge bands were especially sensitive to disease-induced changes in canopy structure and pigment concentration. Indices such NDVI, GNDVI, Cired-edge, and PRI exhibited strong correlations with early stress signals, implying that orchard-scale disease detection might be successfully attained via satellite-based monitoring. The lower spatial resolution of satellite imagery, however, presented difficulties in detecting mild leaf-level infections; hence, integrated approaches fusing UAV and satellite data for multi-scale surveillance were highlighted.

Field spectrometer measurements in some investigations showed reference spectral patterns including carotenoid characteristics, chlorophyll absorption depressions (about 450 nm and 680 nm), water absorption peaks, and NIR reflectance sensitivity to structural deterioration. Diseased mango leaves always exhibited lower NIR reflectance, increased red reflectance, and changes in particular narrow-band indexes including NDVI, PRI, NDRE, and disease-specific hyperspectral ratios. Calibrating machine learning algorithms employed on Sentinel-2, drone multispectral cameras, or hyperspectral images required these spectral changes. Deep learning models—including hybrid CNN-LSTM designs and CNNs—exhibited markedly greater sensitivity in differentiating early-stage illness symptoms than models trained only on RGB drone photographs when spectrometer-derived spectra were employed as training data.

Due to capacity to learn hierarchical representations, deep learning techniques

always surpassed machine learning models in identifying symptoms of early and advanced disease. Performance was even further improved by the inclusion of transfer learning, which let scientists use strong feature extractors pre-trained on enormous image collections. Hybrid architectures using CNN-based feature extraction together with SVM or Random Forest categorization improved decision boundaries in several instances, particularly for datasets including overlapping disease symptoms. Although these achievements are evident, there are still obstacles, including variations in leaf orientation, little public datasets, and erratic light conditions across field surveys. Few studies looked at how well models performed under actual orchard circumstances including occlusions, partly damaged leaves, or mixed disease incidents. Furthermore, geospatial integration approaches are still developing; little research has concentrated on the fusion of UAV spectral data, thermal imaging, and temporal satellite observations. Although present models are extremely precise under controlled conditions, the general results of the reviewed literature stress that operational readiness requires more advances in data diversity, multimodal data fusion, and real-time system deployment.

### Conclusion

This assessment proves that the fusion of geospatial technologies, remote sensing datasets and machine learning techniques has revolutionized mango leaf disease diagnosis by providing a reasonable accurate, scalable and early treatment at both leaf and tree level. High resolution UAV imagery, multispectral and hyperspectral satellite data such as Sentinel-2, Landsat 8/9 and advanced preprocessing workflows (normalization, de-noising, data augmentation, feature extraction-based on indices and texture descriptors) together improve the sensitivity for detecting subtle spectral and structural variations induced by diseases like anthracnose, powdery mildew, dieback or micronutrient deficiencies. Machine learning and deep learning algorithms such as CNNs, SVM, Random Forest and hybrid models have successfully demonstrated a high level of classification accuracy in well designed, spectrally rich data sets. One significant development in recent research is the use of portable spectrometers and field-based spectroscopy, from which accurate leaf-level reflectance signatures can be obtained for these study leaves, proving the ground-truth reference required to calibrate and validate disease models based on remote sensing. Spectrometer-

based spectra increase the stability of vegetation indices, improve feature selection and substantially increase model generalization among different orchards and environmental conditions. The multiscale integration of leaf-, UAV-canopy level, and satellite-field level via the machine learning technology ultimately results in increased robustness of disease detection frameworks providing orchardists detailed knowledge on spatial patterns, severity rates, and progression dynamics. This broad integration of spectroscopy, GIS information, and smart classification systems represents a significant leap towards precision horticulture with the potential to provide early intervention and therefore better crops protection.

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