2025 Term Paper Project HW-4

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1. Problem Definition

Natural leaves exhibit multi-scale surface patterns—including vein networks, pigment gradients, micro-textures, and irregular surface geometries—that influence functional behaviors such as friction, wettability, material degradation, and structural anisotropy. Comparable properties in engineered surfaces are typically controlled through intentional textures such as dimples, ridges, grooves, or hybrid roughness structures. Despite these parallels, the quantitative connection between natural leaf-surface patterns and engineering texture descriptors remains underexplored.

This study aims to analyze leaf-surface patterns using computational, image-based techniques and to translate biological surface variability into engineering-relevant metrics. Although the dataset contains tomato leaves in various physiological conditions, the associated labels are interpreted not as agricultural disease categories but as indicators of distinct natural surface-pattern states. Machine-learning methods—particularly convolutional neural network (CNN) feature extraction—are employed to learn high-dimensional texture representations, while classical texture metrics provide interpretable engineering parameters such as roughness proxies, anisotropy measures, and fractal complexity. Through the integration of these approaches, the research identifies structural relationships among natural textures and evaluates how these reflect engineered surface characteristics.

The initial direction of this project centered on the detection of tomato leaf diseases; however, the feedback I receive on HW1 is that 2025 Term Paper Project emphasizes the analysis of natural surface patterns rather than agricultural diagnostics. Consequently, the project was reframed to reinterpret the same dataset from an engineering perspective. Each leaf condition is now regarded as a unique expression of natural texture variation—manifested through differences in roughness, pigment distribution, directional structure, and multi-scale geometry. This refinement aligns the research with the course objective of translating biological surface structures into engineering-relevant descriptors while still leveraging the richness and diversity of the PlantVillage dataset. The revised focus ultimately enhances the contribution of this work to the understanding of natural surface patterns and their potential applications in surface engineering and biomimetic texture design.

2. Literature Review

Natural surfaces exhibit multi-scale geometric and textural patterns that arise from biological growth and environmental adaptation. These structures—including vein networks, epidermal textures, and micro–nano irregularities—strongly influence functional properties such as friction, lubrication, wettability, and wear resistance. Engineering studies have shown that surface performance is closely tied to measurable parameters such as roughness, anisotropy, and spatial distribution of features. Pawlus et al. established a classification framework for surface texture parameters, and Ruzova et al. emphasized that 3D surface measurements offer more realistic characterization than traditional 2D metrics.

Biomimetic research has demonstrated that natural surface patterns can inspire high-performance engineered textures. Prior studies reported that bio-inspired micro- and nano-patterns improve lubrication, corrosion resistance, and tribological behavior in engineered materials. These findings highlight the potential of natural surfaces—such as leaves, shells, and skins—as models for functional texture design, where geometry directly governs performance.

Despite advances in engineered surface design, natural leaf textures remain underexplored in engineering contexts. Their hierarchical structures, pigment variations, and vein geometries provide a rich set of naturally optimized patterns. This study addresses this gap by quantitatively analyzing leaf-surface textures using computational methods and translating them into engineering-relevant descriptors such as fractal dimension, anisotropy, and spatial complexity.

3. Methodology

This study develops a computational framework for analyzing leaf-surface textures as natural examples of engineering-relevant surface patterns. The overall process begins with acquiring leaf images, preparing them for analysis, extracting both traditional and deep-learning–based texture features, and finally interpreting these features in terms of engineering surface parameters. Rather than treating the dataset as a collection of disease categories, the study interprets each class as a distinct form of natural surface variation. This reframing allows the leaf images to function as a diverse library of naturally occurring patterns, reflecting differences in roughness, anisotropy, pigment distribution, and multi-scale texture complexity.

The images used in this study come from the PlantVillage tomato leaf dataset. Although the dataset includes labels traditionally associated with plant diseases, these labels are treated simply as indicators of different texture states rather than biological diagnoses. Each category—whether it reflects discoloration, lesion formation, aging, or environmental stress—produces visually distinct patterns on the leaf surface. These variations provide an opportunity to examine how natural surfaces change their roughness and geometry across conditions. Before analysis, each image is standardized to a fixed size and converted to grayscale to ensure uniformity across the dataset. Background regions are removed using color masking so that measurements reflect the leaf surface rather than external artifacts. A median filter is applied to reduce noise while preserving important texture features such as veins and intensity transitions.

To translate the leaf images into engineering-relevant information, the study extracts multiple forms of texture descriptors. Traditional surface-analysis methods such as the gray-level co-occurrence matrix (GLCM) are used to quantify roughness-related and directional properties of the surface. Metrics including contrast, entropy, correlation, and homogeneity capture how pixel intensities vary across space, reflecting characteristics analogous to engineered surface parameters like roughness, irregularity, and anisotropy. In addition to these statistical descriptors, fractal dimension is computed using a box-counting approach to represent the multi-scale complexity of the texture. Leaf veins, which form one of the most defining structural elements on the leaf surface, are also analyzed through edge detection and skeletonization. Their geometric properties—such as branching density and directional orientation—offer further insight into natural microstructures that resemble engineered surface channels or grooves.

Beyond these classical descriptors, the study incorporates a convolutional neural network (CNN) to capture higher-level representations of leaf-surface patterns. A pretrained MobileNetV2 model is used as a feature extractor, producing a high-dimensional embedding for each image. These embeddings are not tied to specific engineering parameters, but they encode complex interactions among color variations, edge configurations, and multi-scale textures. By combining CNN-based features with traditional texture descriptors, the analysis merges interpretable surface metrics with the representational power of deep learning, allowing both engineered and naturally learned characteristics to be compared within the same analytical space.

To integrate all extracted features, principal component analysis (PCA) is applied to reduce dimensionality and reveal the dominant axes of variation in leaf-surface textures. The transformed feature space—referred to as the “texture space”—allows relationships among different leaf patterns to be visualized and compared. Within this space, clustering methods such as k-means and hierarchical agglomerative clustering are used to identify coherent groups of patterns. Instead of relying on disease labels, the clusters emerge directly from the statistical structure of the texture space, offering an unbiased view of how natural surfaces organize into families of similar patterns.

The final stage of the analysis relates these clusters back to engineering surface characteristics. By examining the average GLCM metrics, fractal dimensions, vein geometry, and CNN embeddings within each cluster, the study interprets how natural surfaces express properties relevant to engineered systems. For instance, clusters characterized by high contrast and high fractal dimension correspond to rough, irregular surfaces that may promote friction or diffusion. Clusters with strong directional vein structures resemble engineered anisotropic textures designed for lubrication pathways or directional wear behavior. Through this interpretive process, the study bridges natural-surface variation and engineering surface design, demonstrating how biological textures can inform the development of functional engineered surfaces.