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Severity-based analysis of cassava leaf diseases for precision agriculture using image processing

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Abstract: Cassava is a critical food security crop in many tropical regions; however, its productivity is constrained by foliar diseases, including bacterial blight, brown spot, green mite infestations, and cassava mosaic disease. While accurate and timely assessment of disease severity is essential for effective crop management, most existing image-based approaches focus on disease detection rather than quantitative severity estimation. This study presents a lightweight image-processing framework for pixel-level estimation and comparative analysis of cassava leaf disease severity using RGB (Red, Green, and Blue) images. The framework segments cassava leaves using HSV (Hue, Saturation, Value) colour thresholding, identifies diseased regions through clustering in the LAB (Lightness, A-channel, B-channel) colour space, and quantifies disease severity as the ratio of infected pixels to total leaf area. Severity levels are classified as low, medium, or high to support agronomic decision-making. Experimental results across four cassava leaf conditions demonstrate distinct and quantifiable differences in disease severity. Bacterial blight had the highest mean severity (11.3%), indicating extensive infection, followed by brown spot (9.8%), while green mite and mosaic showed lower mean severities (8.5%). Analysis of severity levels showed that infections in the dataset were limited to low and medium categories. Bacterial blight accounted for most medium-severity cases, while green mite and mosaic were mainly mild. The proposed framework is computationally efficient, interpretable, and suitable for resource-limited farming environments. By providing quantitative severity metrics and spatial heatmaps rather than basic disease labels, it supports evidence-based prioritisation and precision crop management.

Keywords: Cassava, HSV thresholding, LAB thresholding, Severity classification, Image processing

1. Introduction

More than 800 million people worldwide rely on cassava (Manihot esculenta Crantz) as a staple crop for their food security and livelihoods; in sub-Saharan Africa and Southeast Asia, this reliance is especially strong (Lilhore et al., 2022; Ramcharan et al., 2019). It is particularly important under variable climatic conditions because of its drought resistance and ability to grow successfully in low-fertility soils (Too et al., 2019). However, foliar diseases and pests such as cassava bacterial blight (CBB), cassava brown streak disease (CBSD), cassava green mite (CGM), and cassava mosaic disease (CMD) pose major challenges to cassava

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productivity. If these biotic stressors are not identified and treated, they may result in significant yield losses (Ramcharan et al., 2019; Oyewola et al., 2021). Visual inspection by qualified agricultural specialists and extension staff is the main method used in traditional cassava disease assessment. This approach is labor-intensive, time-consuming, subjective, and challenging to scale across vast, remote farming areas, despite its effectiveness in limited settings (Ramcharan et al., 2019). To overcome these limitations, computer vision and artificial intelligence (AI), particularly deep learning (DL), have been increasingly used to diagnose plant diseases from leaf images automatically. Due to their ability to automatically extract discriminative visual features without manual feature engineering, deep convolutional neural networks (CNNs) have emerged as the predominant method (Ramcharan et al., 2019; Shoaib et al., 2025). For the identification of plant diseases across a variety of crops, numerous studies have demonstrated excellent classification performance using contemporary CNN architectures such as ResNet, DenseNet, MobileNet, EfficientNet, and their derivatives (Too et al., 2019). The DL models, which are frequently based on transfer learning, have shown promising results in the particular context of cassava when it comes to classifying major diseases (such as CBB, CBSD, CGM, and CMD) from field-captured and smartphone-acquired leaf images (Ramcharan et al., 2019; Ye, 2022; Lilhore et al., 2024). These strategies encourage the development of useful, mobile-based solutions that allow farmers and extension workers to spot problems early and take prompt action.

Rather than estimating disease severity levels, the majority of DL-based studies on cassava leaf diseases have focused on binary or multi-class disease presence classification, such as determining whether a leaf is healthy or affected by a specific disease type (Lilhore et al., 2022; Oyewola et al., 2021; Ramcharan et al., 2019). The extent of leaf damage is not quantified by these classification algorithms, which usually provide a categorical label for the disease type. Their usefulness for agronomic decision-making is severely limited by this constraint, as precise assessment of severity is essential for setting intervention priorities, maximizing pesticide or fungicide application rates, scheduling management actions, and tracking disease progression over time (Tewari & Kumari, 2024). YOLO-based techniques have been effectively used in the specialized field of cassava disease analysis to identify and pinpoint symptomatic areas on leaves and stems of important diseases such as CBB, CBSD, CGM, and CMD (Che et al., 2025). Similar YOLO-based approaches have been successfully applied in other domains, such as railway defect detection (Pan, 2026) and wood surface defect analysis (Li, 2026), demonstrating the adaptability of YOLO architectures to irregular and diffuse lesion detection tasks.

The majority of current implementations still do not offer quantitative severity estimates, even though object detection significantly enhances model interpretability by emphasizing exact disease locations and bounding boxes; instead, they mainly concentrate on presence and spatial localization rather than grading the degree of infection within detected regions (Ramcharan et al., 2019). The number of objects detected or the bounding-box area is frequently used as a stand-in for disease severity. However, when symptoms are diffuse, irregularly shaped, or comprise numerous small, widely distributed lesions, these measures do not adequately reflect the actual amount of infected tissue (Tetila et al., 2020; Wang et al., 2022). The percentage of diseased pixels relative to total leaf area is calculated using segmentation-based methods, which provide a more agronomically useful measure of disease severity. To assess disease severity across a variety of crops, traditional image processing methods such as color thresholding, k-means clustering, region growth, and morphological operations have been widely used (Barbedo, 2019; Singh et al., 2021; Tetila et al., 2020). These techniques typically don't require big training datasets, are computationally light, and are interpretable. Nonetheless, they are susceptible to changes in background complexity, shadows, lighting, and leaf surface characteristics (Barbedo, 2019; Singh et al., 2021).

In defining disease-affected areas and allowing for accurate severity quantification, more recent DL-based semantic segmentation models such as U-Net, Mask R-CNN, DeepLabv3+, and their variations have shown noticeably greater accuracy (Boulent et al., 2019; Wang et al., 2022; Zhang et al., 2023). Although these models perform well, their adoption in low-resource agricultural settings and smallholder farming contexts is severely limited because they usually require pixel-level annotations, very large annotated datasets, and significant computational resources for training and inference (Zhang et al., 2023). Compared to tasks involving object detection and disease classification, quantitative severity estimation has received significantly less attention in cassava-specific research. There is a continuing need for useful, field-deployable, severity-aware assessment methods because most research still places greater emphasis on determining the presence or type of disease than on its extent (Lilhore et al., 2022; Ramcharan et al., 2019; Tetteh et al., 2022). These drawbacks highlight the necessity of resource-efficient, interpretable, and lightweight techniques that can measure the severity of cassava disease without requiring computationally demanding deep neural

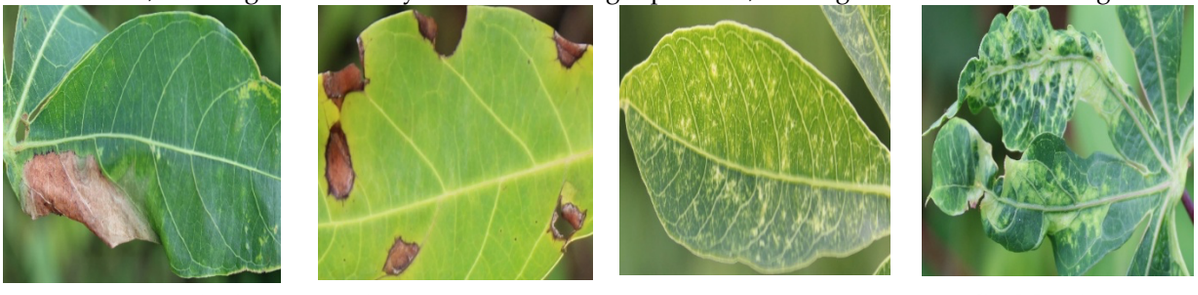
networks or extensive pixel-level annotations. This study's conventional image-processing framework fills this gap by accurately extracting disease-affected regions through pixel-level severity estimation using HSV (Hue, Saturation, Value)- based leaf segmentation and LAB (Lightness, A-channel, B-channel) color space clustering.

The proposed approach aims to supplement, not replace, current DL and YOLO-based detection systems by combining severity quantification, geographic heatmap display, categorical severity classification (Low, Medium, and High), and statistical reporting. The approach offers a useful addition to cassava disease assessment and integrated management by emphasising quick deployment, repeatability, and adaptability for low-resource agricultural settings.

2. Methodology

2.1. Dataset

The dataset used in this study was obtained from the Kaggle repository (https://github.com/icassava/fgvcx-icassava), which is publicly available. It consists of four disease classes: cassava bacterial blight, cassava brown streak, cassava green mite, and cassava mosaic disease, as shown in Figure 1. Each class contains 1,000 images, for a total of 4,000 images. This study utilised 700 images per class, making a dataset of 2800 images.



a) Bacteria-leaf-blight b) Brown-spot c) Green mite d) Mosaic

Figure 1: Images of cassava diseases used in this study:

2.2. Preprocessing method

The preprocessing method begins with an RGB (red, green, and blue) image of a cassava leaf taken under natural field conditions. These images often contain background elements, uneven lighting, and colour variations that can hinder disease analysis (Sathishkumar & Geetha, 2025; Singh et al., 2021). To address this, the image is segmented to separate the leaf from the background; see Figure 2. Colour-based thresholding in an appropriate colour space isolates the green leaf region and removes non-leaf pixels. This ensures that further analysis focuses solely on the leaf surface, improving reliability and reducing the influence of background artifacts on disease measurement.

2.3. Segmentation

After isolating the leaf, the system segments diseased regions within it. The segmented image is converted to a colour space that enhances contrast between healthy and diseased tissue, allowing clear separation of affected areas see Figure 2. The resulting disease mask highlights infected regions and reduces noise. This mask is superimposed on the original image to visualise affected areas, and disease severity is calculated as the proportion of diseased pixels to total leaf area. This method provides both a clear visual representation of disease distribution and a quantitative severity metric for assessment and decision-making.

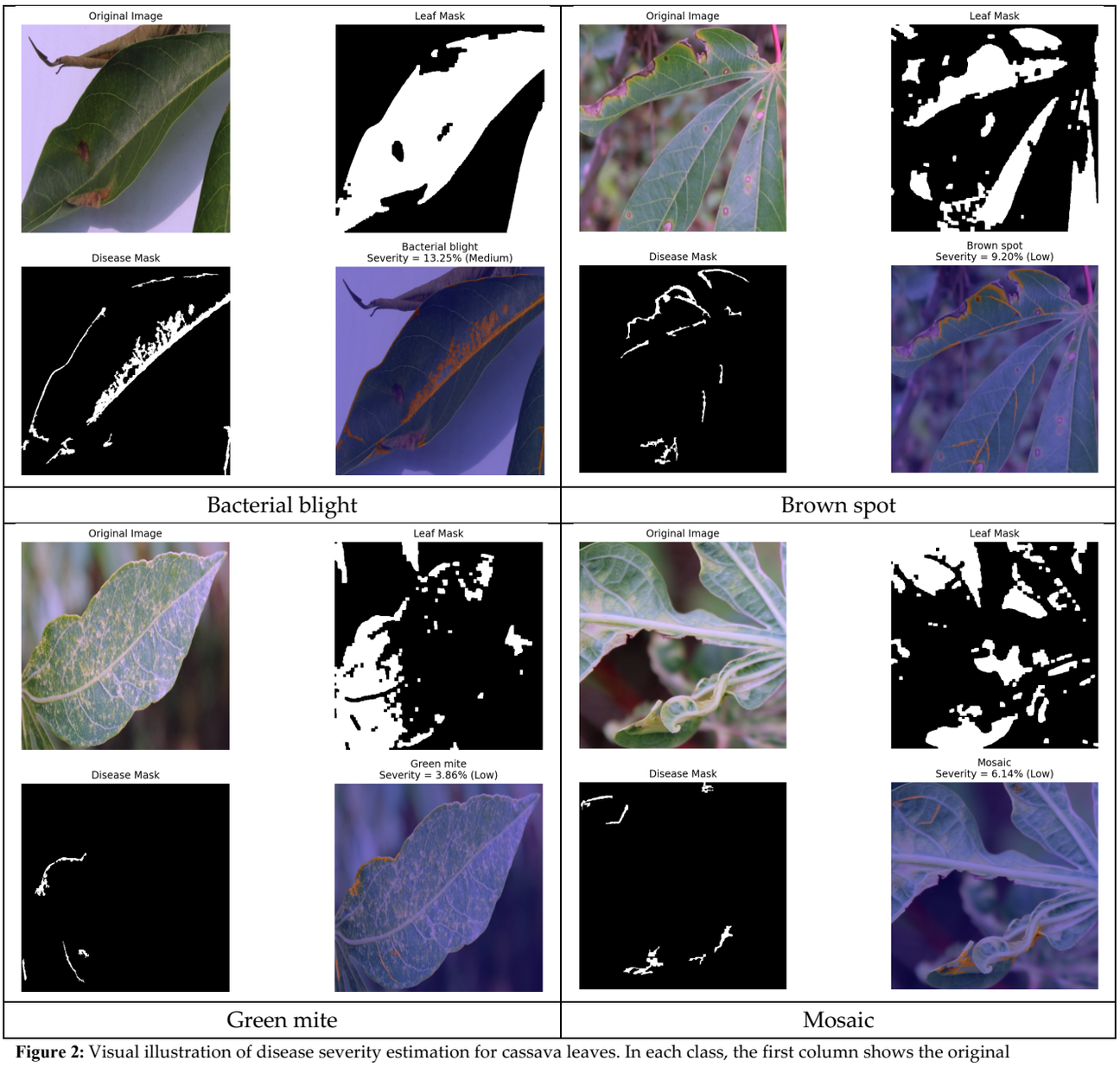


Figure 2: Visual illustration of disease severity estimation for cassava leaves. In each class, the first column shows the original image, followed by leaf segmentation and disease segmentation masks. The last column shows the disease overlay along with the computed data.

2.4. Work Flow

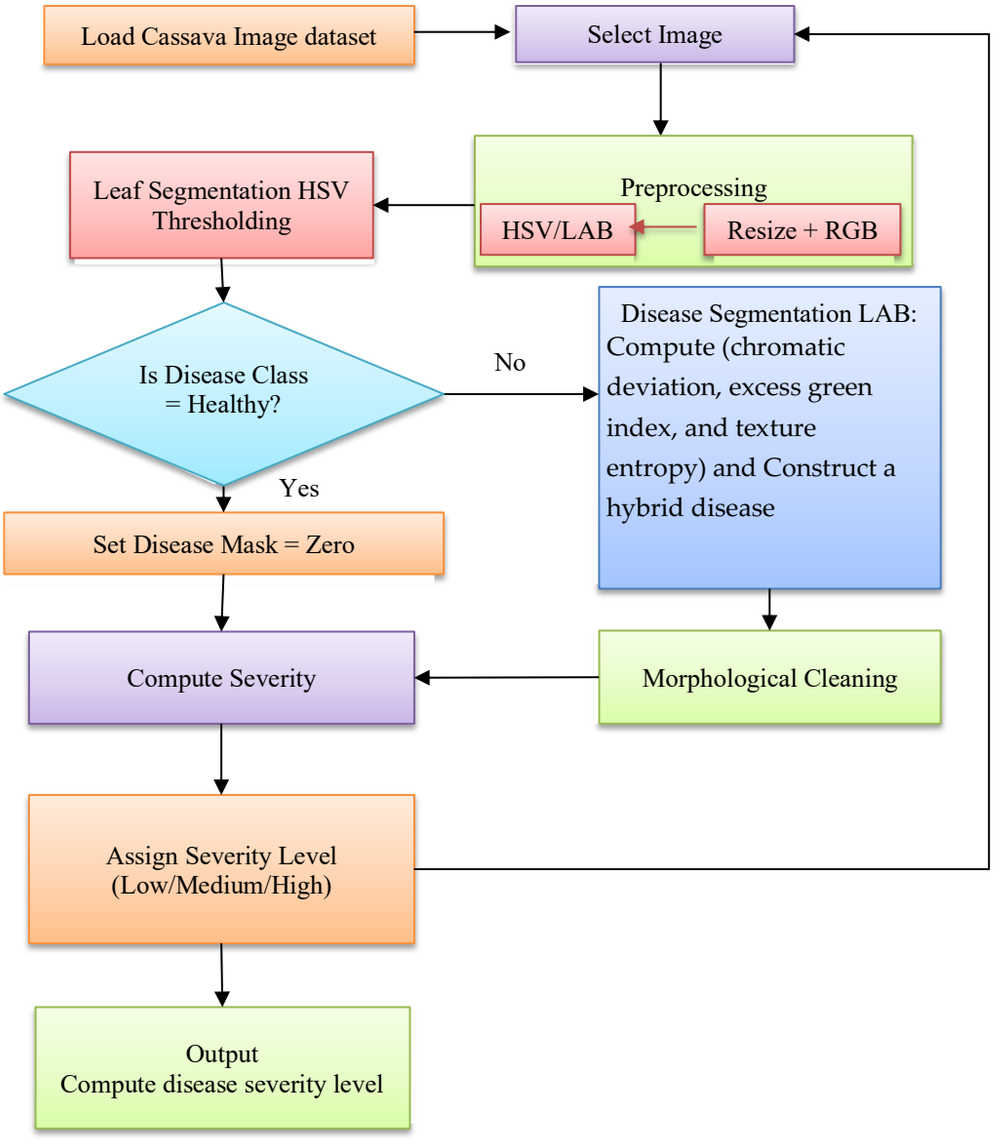
Figure 3 shows the workflow for this study. The system loads a dataset of cassava leaf images, including both healthy and diseased samples from farms or field surveys. Each image is processed individually to ensure consistent analysis and reliable results. Before analysis, each image is preprocessed by resizing to a standard dimension and converting colours to formats that separate the leaf from the background and highlight disease-related changes. This step improves the accuracy of later operations. The system then segments the leaf by isolating it from the background, such as soil or sky. This prevents irrelevant regions from affecting disease measurements.

After segmentation, the system determines whether the leaf is healthy. If so, it assigns a zero-disease mask to prevent unnecessary processing and accurately report healthy leaves as disease-free. If the leaf is unhealthy, the system identifies abnormal areas, such as spots, discolouration, or damage, and removes small or noisy regions that do not indicate actual symptoms, thereby improving detection quality. This section computes three methods: chromatic deviation, excess green index, and texture entropy, to detect four classes, as detailed in *Algorithm 1*. Chromatic deviation detects brown spot and blight, excess green index detects mosaic, and texture entropy detects green mite. These methods were chosen because disease patterns vary across crops, especially for green mite and mosaic.

After identifying diseased areas, the system calculates severity by comparing the size of affected regions to the total leaf area. The resulting percentage quantifies disease intensity. The system then assigns a severity

level of low, medium, or high based on the percentage calculated by *Algorithm 1*. These categories help farmers and agricultural officers make informed decisions.

Finally, the system provides the disease severity percentage, severity level, and a visual highlighting of the affected areas on the leaf.



Algorithm 1: Automated Severity Estimation and Spatial Analysis of Cassava Leaf Diseases

Figure 3: Shows the workflow for this study

Input: Cassava leaf image dataset $D = \{I_1, I_2, I_3, \ldots . I_N\}$ organized by disease class
Output: Disease severity percentage, severity level (Low/Medium/High)

Step 1: Load cassava image dataset D
Step 2: For each image $I_i \in D$

Step 2.1: Resize image to a fixed resolution

$$I_i \rightarrow I_i^r \in \mathbb{R}^{512x512x3}$$

Step 2.2: Illumination normalisation to reduce lighting bias and reflection effect

Apply Gray-world color constancy

$$I_c' = I_c \times \frac{\mu_{gray}}{\mu_c}$$

Where:

$$c \in \{R, G, B\},$$

$$\mu_c = mean\ intensity\ of\ channel\ c$$
$$\mu_{gray} = (\mu_R + \mu_G + \mu_B)/3$$

Step 2.3: Convert to HSV and LAB color space

$$HSV_i = f_{HSV}(I_i')$$
$$LAB_i = f_{LAB}(I_i')$$

Step 2.4: Leaf segmentation

Apply HSV-based green thresholding

Leaf Mask:

$$M_{leaf}(x,y) = \begin{cases} 1, & HSV \in [H_{min}, H_{max}] \\ 0, & otherwise \end{cases}$$

Where:

$$M_{leaf} \in \{0,1\}^{H \times W}$$

Apply morphological closing and opening to remove background noise

Compute total leaf pixels:

$$N_{leaf} = \sum M_{leaf}$$

Step 2.5: Disease detection

If the image belongs to the healthy class:

Set disease mask:

$$M_{dis} = 0$$

Else:

a) Compute chromatic deviation specifically for brown spot and blight detection

Extract LAB channels:

$$a(x,y), b(x,y)$$

Compute a healthy baseline inside the leaf:

$$\mu_a = mean(a_{leaf}),$$
$$\mu_b = mean(b_{leaf})$$

Chromatic deviation:

$$D(x,y) = \sqrt{(a-\mu a)^2 + (b-\mu b)^2}$$

Normalize:

$$D_n = \frac{D - D_{min}}{D_{max} - D_{min}}$$

b) Compute the excess green index specifically for Mosaic detection

$$ExG = 2G - R - B$$

Normalize:

$$ExG_n = \frac{ExG - ExG_{min}}{ExG_{max} - ExG_{min}}$$

Green loss feature:

$$GL = 1 - ExG_n$$

c) Compute texture entropy specifically for Green mite detection

Convert to grayscale and compute local entropy:

$$T(x,y) = Entropy(I_{gray}, r)$$

Where:

$$r = disk\ radius$$

Normalize:

$$T_n = \frac{T - T_{min}}{T_{max} - T_{min}}$$

d) Construct Hybrid disease index

$$DI(x,y) = 0.4D_n + 0.3GL + 0.3T_n$$

e) Adaptive thresholding

Compute threshold inside the leaf

$$\tau = \mu(DI_{leaf}) + \delta(DI_{leaf})$$

Disease mask:

$$M_{dis}(x,y) = \begin{cases} 1, & DI(x,y) > \tau \Lambda M_{leaf}(x,y) = 1 \\ 0, & otherwise \end{cases}$$

Apply morphological operations to remove noise (small regions)

$$N_{dis} = \sum M_{dis}$$

Step 2.6: Compute disease severity

$$S_i = \frac{N_{dis}}{N_{leaf}} \; x \; 100$$

Step 2.7: Severity level computation

$$L_i = \begin{cases} \text{Low}, & S_i < 10 \\ Medium, & 10 \leq S_i \leq 25 \\ High, & S_i > 25 \end{cases}$$

Step 2.8: Generate a disease severity heatmap by mapping the diseased regions onto the original image, highlighting the spatial distribution of infection intensity

$$Heatmap = Colormap(M_{dis})$$

Overlay: $I_{overlay} = 0.6I_i' + 0.4Heatmap$

Step 2.9: Store the Image name, class label, severity percentage, severity level and heatmap

$$\{I_i, Class_i, S_i, L_i, I_{overlay}\}$$

Step 3: After processing all images:

- compute class-wise statistics, including

$$\bar{S}_k = \frac{1}{n_k} \sum S_i$$

Where:

$$n_k = number\ of\ images\ in\ class\ k$$

- Compute severity distribution and severity-level frequencies
- Generate comparative visualisation

Return:

Severity results table, spatial heatmaps, and comparative plots for cassava leaf diseases

3. Result and discussion

This section presents the research findings from applying the proposed framework to estimate the severity of cassava leaf disease. Results are organised to highlight quantitative severity measures, disease-class distributions, and comparisons.

3.1. Research findings

Experimental evaluation of the proposed framework reveals statistically significant differences in disease severity among four cassava leaf diseases: bacterial blight, brown spot, green mite infestation, and mosaic disease. This framework enables pixel-level quantification of infected leaf area, enabling direct comparison of infection intensity and distribution patterns across disease classes. The following figures provide analyses of mean severity, distribution trends, and severity-level categorisation results.

Figure 4 compares average disease severity across four cassava leaf diseases. The results demonstrate distinct differences in infection intensity among these diseases. Bacterial blight shows the highest mean severity, at 11.3%, indicating a greater proportion of infected leaf area than the other disease classes. This

finding implies that bacterial blight results in more extensive tissue damage and a greater spatial progression than other diseases. Brown spot has a mean severity of 9.8%, reflecting moderate lesion development but less overall spread than bacterial blight. Green mite and mosaic both display mean severity values of 8.5%, indicating lower levels of leaf area damage. Although green mite primarily affects leaf texture, and mosaic produces chlorotic patterns, their average spatial impact on leaf tissue is of similar magnitude.

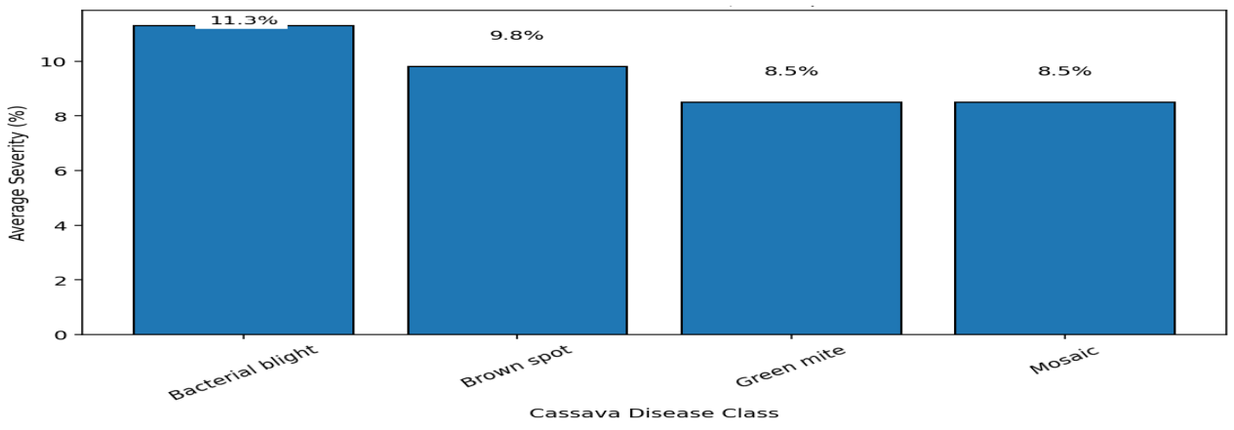


Figure 4: Shows the average disease severity for four cassava leaf diseases

Figure 5 presents trends in the severity distribution of cassava diseases, offering a detailed depiction of infection intensity across the image classes. In contrast to mean-based comparisons, this figure shows the frequency of images within specific severity intervals, thereby clarifying whether infections are primarily mild, moderate, or severe.

Bacterial blight shows a distinct concentration of cases within the 10–20% severity range, corresponding to the highest image frequency. Fewer cases are observed in the 0–5% range, and the frequency decreases markedly beyond 20% severity. These trends indicate that bacterial blight typically results in moderate tissue damage, with extremely severe infections occurring infrequently. Brown spot shows a distinct peak near the 10% severity range, where most images are concentrated. A moderate number of cases are present in the 0–5% range, with only a small proportion exceeding 20% severity. This distribution suggests that brown spot typically appears as moderate necrotic lesions rather than extensive leaf destruction and is less dispersed toward high-severity extremes than other diseases.

Green mite infestation is predominantly clustered within the 5–15% severity range, with a considerable concentration at 10%. Image frequency declines sharply beyond 20% severity, indicating that green mite damage is generally localised and rarely progresses to widespread leaf infection. This pattern is consistent with its biological manifestation as speckled or patchy chlorotic damage rather than aggressive necrosis. Mosaic disease shows a broader spread across the 5–15% severity range, with substantial frequencies in both low (0–5%) and moderate (10–20%) intervals. Although severe cases above 20% are limited, mosaic remains relatively consistent across mild-to-moderate severity levels. This shows its characteristic chlorotic patterning, which often affects substantial portions of the leaf but typically does not result in severe tissue necrosis.

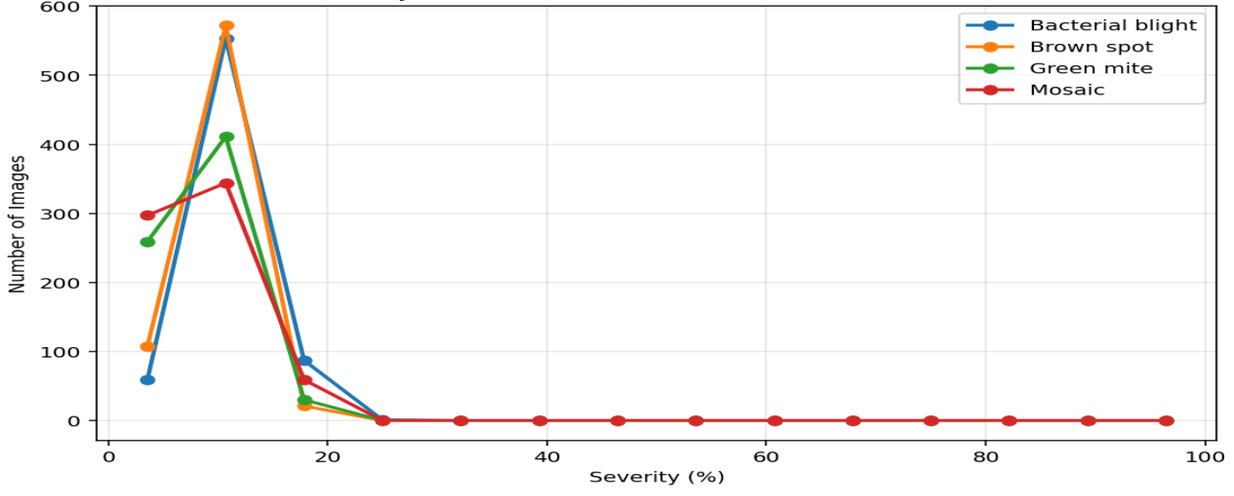


Figure 5: Illustrates the severity distribution trends across four cassava diseases

Figure 6 illustrates the distribution of cassava leaf images across three severity levels: Low, Medium, and High for four distinct diseases. The severity-level distribution heatmap quantifies the number of images classified as Low or Medium severity for each disease. Notably, no images in the dataset were classified as High severity. Therefore, all observed infections are limited to the low-to-moderate severity range. In the case of Bacterial blight, 216 images were classified as Low severity and 484 as Medium severity, out of a total of 700 images. This corresponds to 30.9% (Low) and 69.1% (Medium). The predominance of medium-severity cases suggests that bacterial blight generally causes moderate tissue damage rather than mild infections.

For Brown spot, 371 images were classified as Low severity and 329 as Medium severity, for a total of 700 images. This represents 53.0% (Low) and 47.0% (Medium). The distribution is relatively balanced but slightly favors mild infection levels, suggesting that brown spot more frequently manifests as localised lesions rather than extensive damage.

For Green mite, 487 images were classified as Low severity and 213 as Medium severity out of 700 images, corresponding to 69.6% (Low) and 30.4% (Medium), respectively. This strong predominance of low-severity cases indicates that green mite infestations are generally mild and rarely progress to more extensive damage.

For Mosaic, 462 images were classified as Low severity and 238 as Medium severity, for a total of 700 images, corresponding to 66.0% (Low) and 34.0% (Medium), respectively. Similar to green mite, mosaic disease is primarily characterised by mild infections, with a smaller proportion progressing to moderate severity.

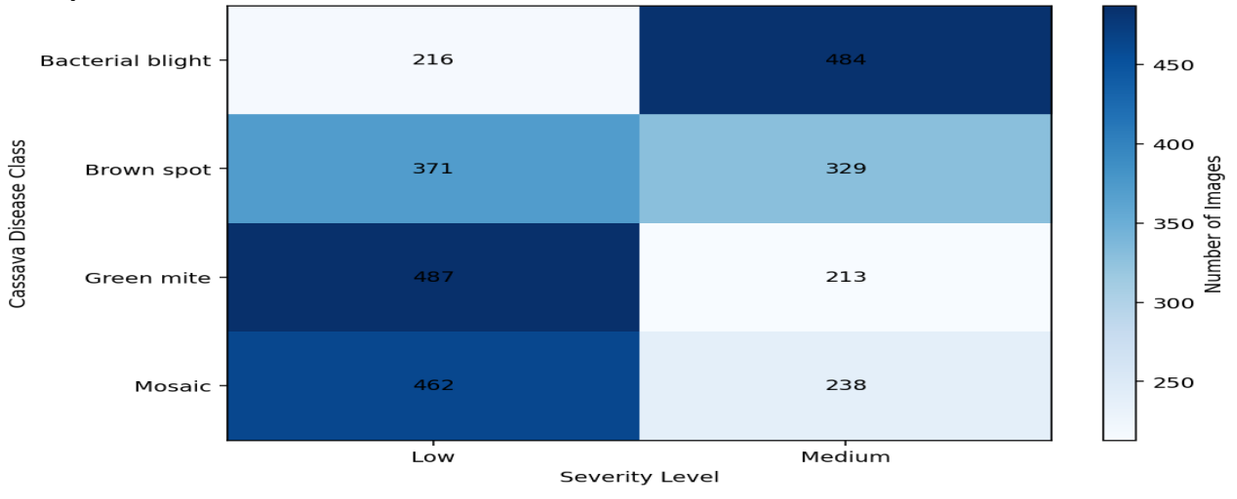


Figure 6: Summarises the distribution of cassava leaf images across three severity levels, Low, Medium, and High, for four cassava diseases

The dataset indicates that cassava diseases in this study are predominantly classified as low or medium-severity, with no high-severity cases. Bacterial blight has the highest proportion of medium-severity cases, whereas green mite and mosaic are mostly associated with low-severity infections. Brown spot falls between, with nearly equal numbers of low- and medium-severity cases. The consistency among severity-level counts, mean severity values, and continuous severity distributions highlights the framework's effectiveness in capturing both the intensity and prevalence of cassava leaf diseases. These results offer practical guidance for prioritising disease management and developing targeted interventions in cassava production. Using severity categories (Low, Medium, High) increases the system's value by translating pixel-level data into actionable agronomic recommendations. Spatial heatmaps further support analysis by showing disease intensity across the leaf, enabling targeted actions such as selective pesticide application.

Unlike object detection methods that only assess disease presence, the proposed approach delivers severity-aware results, which are essential for prioritising crop health. Its low computational complexity and interpretability make it suitable for use in resource-limited and field environments. However, the method may be affected by extreme changes in illumination. Future work could address this by applying illumination normalisation or by integrating hybrid deep-learning segmentation techniques.

3.2. Comparison with other studies

3.2.1. Comparison with General CNN-Based Approaches

This study advances the discourse on plant disease severity estimation by proposing a lightweight, interpretable framework that uses HSV–LAB colour space segmentation and pixel-level quantification. Unlike

many existing approaches that emphasise disease detection, our work explicitly addresses severity estimation, thereby filling a critical gap in precision crop management. A comprehensive review of CNN-based severity assessment is given by Shi et al. (2023), highlighting DL's prowess in identifying intricate visual characteristics. Although the authors acknowledge issues like processing difficulties and the requirement for big annotated datasets, their findings emphasise CNNs as the dominating paradigm. This study's method deviates from this path by showing that colour thresholding and clustering may be used to estimate severity, providing a more approachable option for agricultural contexts with low resources. This methodological difference is important because although CNNs are quite accurate, their use in smallholder settings remains limited, whereas our strategy places greater emphasis on efficiency and interpretability.

Mehta et al. (2023) and Banerjee et al. (2023) integrate sophisticated concepts, including federated learning and hybrid classifiers, such as CNN–SVM, to extend CNN-based severity evaluation to mango leaves and fruits, respectively. Especially in contexts involving remote data, these improvements enhance resilience and flexibility. Nevertheless, they also rely on advanced computing systems. On the other hand, our research highlights the usefulness of lightweight models in situations where access to high-performance computation is restricted, showing that severity estimation can be accomplished without complex architectures. One method emphasises practical scalability, while the other pushes the limits of technological expertise. This comparison shows two complementary paths.

Kifyoga and Ishengoma (2025) employed a CNN trained from scratch to diagnose rice disease. Their main goal was to increase disease classification accuracy so that the system could determine which disease was present in rice leaves. Although this is a major advancement in automated diagnosis, the disease's severity was not measured. Building a DL model from scratch was the main focus, which is computationally taxing and requires substantial training data and resources.

For the categorisation and severity assessment of maize leaf disease, Mafukidze *et al*. (2022) suggest adaptive thresholding of CNN features. Their research, which conceptually supports our pixel-ratio methodology, emphasises the significance of thresholding techniques in assessing severity. However, our study completely eschews DL in favor of direct colour-space analysis, even though their methodology is still includes CNN feature extraction. This distinction demonstrates that severity estimation can be performed both within and outside CNN-based pipelines, highlighting the flexibility of thresholding techniques.

Prior research on CNN-based detection and identification tasks has been the main focus of earlier studies such as Shrestha et al. (2020), Sun et al. (2022), and Gupta et al. (2024). These studies, which frequently give performance indicators like precision and recall, support the trend of giving categorisation accuracy priority. They hardly ever go beyond analysis to quantify severity, though. By treating severity estimation as a distinct analytical need rather than an extension of detection, this work contributes to the conversation. This study's methodology offers practical insights that can direct agronomic actions like pesticide treatment, selective pruning, or prioritising resistant types by classifying severity levels as low, medium, or high.

Agronomic findings on the aggressive spread of bacterial blight in cassava fields are consistent with our finding that the disease had the highest mean severity (11.3%), followed by brown spot (9.8%). On the other hand, because of its less widespread coverage, the mean severity of the green mite and mosaic was lower (8.5%). The study's focus on quantitative severity ratios provides a valuable complement to conventional CNN-based methods, which typically emphasise classification or detection accuracy. By estimating the proportion of infected leaf area, the proposed framework connects visual symptoms to potential yield loss and resource allocation. This severity-based approach extends beyond disease identification to assess agronomic impact, supporting more targeted, evidence-based disease management.

3.2.2. Cassava-Specific Studies

Recent studies focusing on cassava highlight the dominance of CNN-based classification. An improved CNN model for identifying cassava leaf diseases was designed by Lilhore et al. (2022), achieving high accuracy in distinguishing between disease classes. Similarly, Gopi (2024) investigated DL techniques using CNNs and neural networks, and Alado (2024) used SqueezeNet to classify cassava diseases, highlighting the computational efficiency of CNN architectures. The importance of data augmentation in raising the accuracy of cassava disease classification was further illustrated by Thaiyalnayaki et al. (2022). By evaluating CNN models built from scratch and those trained using transfer learning (TL), Kifyoga et al. (2026) extended this line of inquiry to cassava. According to their research, TL typically outperformed CNNs trained from scratch, demonstrating the potential of pre-trained models for greater efficiency and accuracy. Once more, the emphasis was on classification and detection: identifying the disease type and whether cassava leaves were

affected. Although this effort improved the diagnosis of cassava diseases, it did not quantify severity; instead, it focused on category detection.

Collectively, these cassava-specific investigations demonstrate the superiority of CNNs for detection and classification. Instead of measuring severity, they continue to focus on detecting the presence of the disease. By specifically assessing severity levels, our work addresses this gap and enhances detection-focused CNN models. By quantifying severity ratios and classifying them into low, medium, and high levels, this study's methodology offers practical insights that directly inform agronomic decisions. This distinction is key because it enables more accurate management techniques, such as prioritising resistant types or applying pesticides. Only where necessary.

3.2.3 Practical Implications

The framework used in this study is lightweight, making it suitable for use in resource-constrained farming contexts. Smallholder farmers and extension agents can use the method, as it can be implemented with simple hardware, unlike CNN-based approaches that require sophisticated processing resources. Additionally, the interpretability of colour-space segmentation improves usability and trust by enabling non-specialists to comprehend and respond to severity outputs. By categorising severity levels into three groups (Low, Medium, and High), the framework offers useful information for agronomic management. In comparison, detection-only models indicate the presence of a disease but do not assess its severity. Precision agriculture is enhanced by the ability to predict severity ratios, which supports decisions such as pesticide dosing, selective pruning, and prioritising disease-resistant varieties.

4. Recommendations

Quantitative severity analysis shows statistically significant differences in infection intensity and distribution among cassava leaf diseases. Bacterial blight exhibits the highest mean severity and the largest proportion of medium-level infections, indicating a greater impact under these conditions. Brown spot shows moderate severity, with a balanced distribution between low and medium levels, whereas green mite and mosaic are predominantly mild. As there are no high-severity cases in the dataset, management strategies should prioritise bacterial blight, then brown spot. Routine monitoring of green mite and mosaic is still necessary to prevent escalation. Crop disease management techniques should incorporate severity-based decision-making. Instead of relying solely on binary detection techniques, farmers can more accurately coordinate their interventions, whether through pruning, pesticide application, or variety choice, by dividing disease severity into low, medium, and high levels. The proposed severity estimation framework provides a practical basis for severity-driven intervention, enabling more efficient allocation of limited agricultural resources, particularly within smallholder farming systems.

5. Conclusion

In this study, we present an explainable image-processing framework for pixel-level estimation and comparative analysis of cassava leaf disease severity from RGB images. The framework combines HSV-based leaf segmentation, LAB colour-space chromatic deviation analysis, and quantitative severity computation to produce numerical severity indices and spatial heatmaps of infection. Experimental results for four cassava diseases show that bacterial blight had the highest mean severity (11.3%), followed by brown spot (9.8%). Green mite and mosaic had lower mean severities (8.5%). Most infections fell within the 5–20% severity range, with bacterial blight shifting notably toward moderate severity.

All disease samples were classified as Low or Medium severity, with no High-severity cases observed. Bacterial blight had the highest proportion of medium-severity cases (69.1%), while green mite (69.6% low) and mosaic (66.0% low) were mostly mild. Brown spot showed a balanced distribution between low (53.0%) and medium (47.0%) severity. Consistent trends across mean comparisons, distribution curves, and severity heatmaps support the framework's reliability and stability. By progressing beyond simple disease detection to quantitative severity estimation, the proposed method yields agronomically meaningful metrics that facilitate disease prioritisation and support targeted management strategies. Due to its computational efficiency and training-free design, the framework is well-suited for deployment in low-resource agricultural environments.

Future work will focus on improving robustness under varying field illumination and incorporating adaptive colour modelling. Integrating DL-based segmentation may enhance accuracy for complex disease patterns, while temporal severity modelling could enable monitoring of disease progression over time.

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