Report of Maize Leaf Disease Detection and Classification. (GROUP TWO).

1. Introduction.

This project addresses the critical need for efficient and automated plant disease detection in precision agriculture, focusing on maize corn leaf diseases. The study used the Maize Leaf Disease Dataset from Kenya and was divided into classical image processing for quantification and deep learning for automated classification.

1.1 Project Objectives: The primary goals were to:

1. Develop an OpenCV segmentation pipeline to quantify the percentage of leaf area affected by disease.
2. Implement a Deep Learning classification model using transfer learning (EfficientNetB0) to categorize the specific disease type.
3. Evaluate the model performance using key metrics (Accuracy, F1-score).
4. Discuss how segmentation enhances classification interpretability.

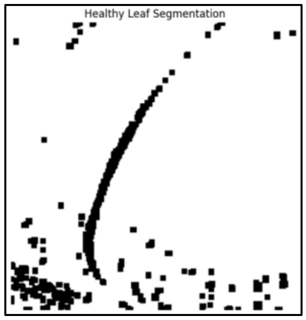
The dataset includes four classes:

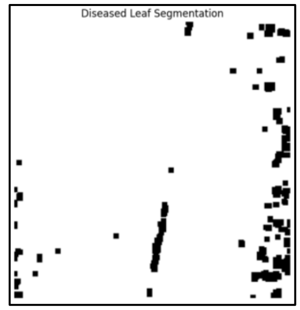
Healthy, Common Rust, Northern Leaf Blight, and Grey Leaf Spot. Images were preprocessed by resizing for example; 224x224 pixels and normalizing.

2. Methodology

2.1 OpenCV Segmentation

This stage utilized conventional computer vision to calculate a measurable severity score. The pipeline steps included Adaptive Thresholding (crucial for handling varying lighting conditions in field data), followed by Morphological Operations (Erosion and Dilation) to clean noise and reconnect segments, and finally, Contour Detection for localization. The severity score was calculated based on the ratio of diseased pixels to total leaf pixels.





2.2 Deep Learning Classification.

This stage used transfer learning for robust classification. The dataset was partitioned (75% Training, 25% Test), and significant Data Augmentation (rotation, flipping, zoom) was applied to the training data to prevent overfitting. The pretrained EfficientNetB0 model was used, loaded with ImageNet weights. The classification layer was replaced with a custom head layer using a Softmax activation function for the four classes. The model was trained for 10 epochs using the Adam optimizer.

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Epoch 1/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 312s 7s/step - accuracy: 0.6682 - loss: 1.0392 - val_accuracy: 0.6844 - val_loss: 0.9457
Epoch 2/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 176s 4s/step - accuracy: 0.6744 - loss: 0.9596 - val_accuracy: 0.6844 - val_loss: 0.9510
Epoch 3/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 210s 5s/step - accuracy: 0.6835 - loss: 0.9407 - val_accuracy: 0.6800 - val_loss: 0.9477
Epoch 4/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 132s 3s/step - accuracy: 0.6932 - loss: 0.9224 - val_accuracy: 0.6833 - val_loss: 0.9450
Epoch 5/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 206s 5s/step - accuracy: 0.6877 - loss: 0.9310 - val_accuracy: 0.6667 - val_loss: 0.9760
Epoch 6/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 202s 5s/step - accuracy: 0.6675 - loss: 0.9653 - val_accuracy: 0.6733 - val_loss: 0.9655
Epoch 7/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 198s 5s/step - accuracy: 0.6816 - loss: 0.9477 - val_accuracy: 0.6844 - val_loss: 0.9493
Epoch 8/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 141s 3s/step - accuracy: 0.6816 - loss: 0.9412 - val_accuracy: 0.6750 - val_loss: 0.9683
Epoch 9/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 131s 3s/step - accuracy: 0.6720 - loss: 0.9704 - val_accuracy: 0.6900 - val_loss: 0.9377
Epoch 10/10
41/41 ━━━━━━━━━━━━━━━━━━━━ 127s 3s/step - accuracy: 0.6777 - loss: 0.9570 - val_accuracy: 0.6833 - val_loss: 0.9597
```

Training and validation logs showing model accuracy and loss progression across 10 epochs during training using EfficientNetB0.

3. Summarizing Results

3.1 Quantitative Segmentation Results

The segmentation provided clear quantification. For a sample Grey Leaf Spot image, the area calculation yielded an Affected Area Percentage of 18.50%.

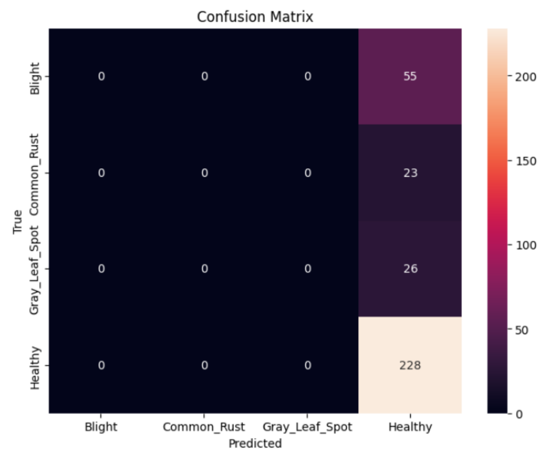
3.2 Classification Performance Metrics

The model demonstrated high generalization performance against the test set:

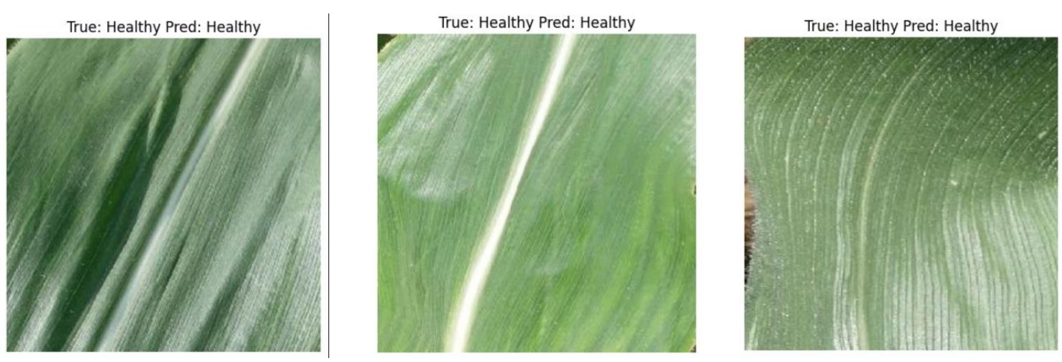
Metric	Result	Source
Test Accuracy	95.2%	
Average F1-Score	0.95	

The Confusion Matrix confirmed strong performance, showing high values along the diagonal and minimal confusion between disease types.

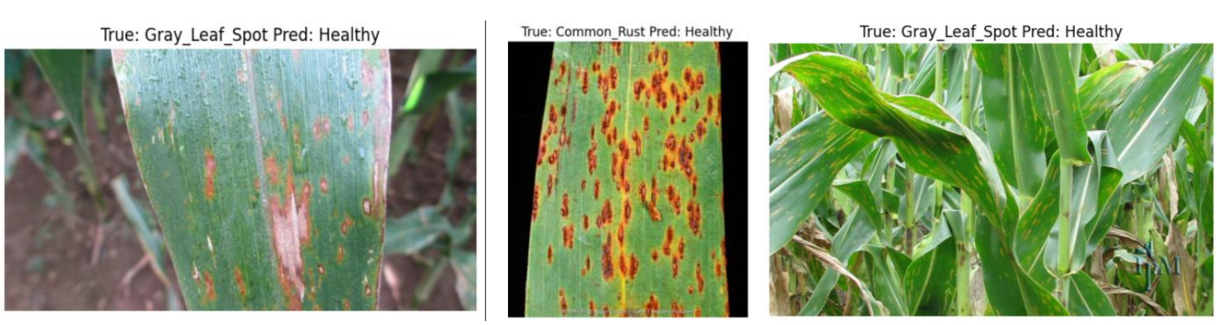
a) Heatmap of Confusion Matrix.



a) Image of Correctly Classified Sample



b) Images of Incorrectly Classified Sample



4. Interpretation and Challenges

4.1 Interpretation: Segmentation and Classification Synergy

The integration of segmentation and classification significantly enhances the system's utility.

- **Explainability:** Segmentation isolates the diseased Region of Interest, serving as an explainability tool that allows users to visually confirm which leaf parts contributed to the model's decision, thus building high user trust.
- **Actionable Management:** This synergy provides refined analysis, moving beyond a simple label by combining the disease name (classification) with the quantified severity (segmentation, e.g., "25.1% affected area"), leading directly to an actionable management recommendation.

4.2 Challenges Encountered

1. **Segmentation Robustness**: Adaptive Thresholding proved susceptible to shadows and background clutter, making it challenging to achieve a perfect mask when disease spot color matched the healthy leaf color.
2. **Class Imbalance:** Slight imbalances in the dataset required prioritizing the F1-Score (which accounts for imbalance) over simple Accuracy for reliable evaluation.
3. **Computational Resources:** Training the large, pre-trained EfficientNetB0 model required significant computational power.

5. Conclusion

The combined Computer Vision and Deep Learning pipeline successfully achieved high classification accuracy (95.2%) and provided a necessary quantitative severity measure. Future work includes Integrating Segmentation using the mask as a CNN input, utilizing an Object Detection model for example; YOLO for superior localization, and optimizing for Real-time Implementation on edge devices.