Detecting Farmland Conditions with Classical Computer Vision: Standing Water, Weed Clusters, and Nutrient Deficiency

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Abstract

This report explores the use of classical computer vision techniques for agricultural scene understanding in aerial imagery. Focusing on several binary classification tasks related to farmland conditions, we investigate interpretable, lightweight pipelines built around feature engineering and traditional machine learning, rather than deep neural networks. Our approach leverages contrast enhancement, statistical descriptors, and texture-based features to represent visual patterns linked to environmental and crop health indicators. Using k-Nearest Neighbors (k-NN) as a baseline classifier and cross-validation for model selection, we evaluate the effectiveness of these handcrafted features under varying conditions. Results show that classical pipelines, when carefully designed, can achieve competitive performance while remaining computationally efficient and transparent. This work highlights the continued relevance of interpretable computer vision methods for resource-constrained and data-limited agricultural applications, and provides reproducible tools to support future experimentation and benchmarking.

1 Introduction

Agricultural monitoring through aerial imagery has become increasingly important for sustainable farming practices. The Agriculture-Vision Challenge brings together researchers to improve the diagnosis of farmland conditions through automated image analysis. This work addresses three binary image-level classification problems on near-infrared (NIR) patches: presence of standing water, weed clusters, and nutrient deficiency.

We train independent binary classifiers per condition. Dataset sizes from the challenge label files are: standing water (1,071 positives, 3,213 negatives), weed clusters (5,941 positives, 17,823 negatives), and nutrient deficiency (8,028 positives, 24,084 negatives). All images are 512×512 pixels and exhibit notable class imbalance for weeds and nutrients.

We intentionally avoid deep learning and focus on classical computer vision with k-Nearest Neighbors (k-NN), emphasizing interpretability and low computational cost.

2 Background

Agriculture is a cornerstone of global economic development and food security, contributing substantially to national economies such as India's, where it accounts for approximately 17.9% of the GDP. As the global population grows, improving agricultural productivity while minimizing resource waste has become a critical challenge. Technological advances in agricultural monitoring—particularly through remote sensing and computer vision—offer the potential to identify crop stress, nutrient deficiencies, and other field conditions more efficiently than traditional manual inspection. Nutrient levels play a vital role in crop growth, and deficiencies often manifest through visible characteristics such as leaf color and texture. Automated recognition of these patterns enables more precise nutrient management, ultimately improving yield and sustainability. (Jose et al. 2021)

Recent research in agricultural image analysis has been dominated by deep learning, yet these models often demand large annotated datasets, extensive computational resources, and offer limited interpretability. To address these challenges, our work focuses on classical, interpretable computer vision methods that provide lightweight, transparent alternatives. Using the Agriculture-Vision 2021 dataset, which contains diverse aerial farmland imagery, we design pipelines for three binary classification tasks: detecting standing water, weed clusters, and nutrient deficiency. Our approach emphasizes feature engineering over end-to-end learning—extracting intensity histograms, local contrast measures, and statistical summaries to capture meaningful visual structure. These features are used within a k-Nearest Neighbors (k-NN) framework, chosen for its simplicity and interpretability.

Through systematic cross-validation and threshold tuning, we evaluate the performance of these pipelines under varying agricultural conditions. This study demonstrates that well-engineered classical models can serve as strong baselines for agricultural vision tasks, combining transparency, reproducibility, and computational efficiency. Such methods are particularly valuable for resource-limited settings, where access to large-scale data and high-end hardware is constrained, yet actionable insights into crop health are essential.

3 Experiments

Data Preprocessing

Image Loading and Organization The dataset consists of NIR band images stored in JPEG format. For each task, we load labels from the corresponding text files in data/labels:

```
water_positives.txt
water_negatives.txt
weed_cluster_positives.txt
weed_cluster_negatives.txt
nutrient_deficiency_positives.txt
nutrient_deficiency_negatives.txt
```

We then build per-task data frames of image names and binary labels, preserving the original class distributions.

Brightness and Contrast Normalization All tasks normalize intensity distributions to mitigate illumination and sensor variability. For our models, we use contrast-limited adaptive histogram equalization (CLAHE) via `exposure.equalize_adapthist()` and additionally include a binary low-contrast indicator from `exposure.is_low_contrast()` as a feature.

Feature Engineering

We designed specific feature sets that balance informativeness and dimensionality.

Features Used

- **Low-contrast flag**: Binary feature from `is_low_contrast`.
- **CLAHE histogram**: 16-bin intensity histogram on the CLAHE-equalized image, L1-normalized.
- **Statistical descriptors**: Same 8 summary statistics as above.

Total: 25 features per image (1 + 16 + 8).

Model Development

Train-Test Split and Scaling For each task we split the data into training (80%) and testing (20%) sets using stratified sampling to maintain class balance. Features are standardized with `StandardScaler` to zero mean and unit variance prior to k-NN.

k-Nearest Neighbors We use k-NN as the sole classifier family. We explore $k \in \{3, 5, 7, 10, 15, 20\}$ and compare Euclidean vs. Manhattan distances as well as uniform vs. distance weighting. Model selection uses 5-fold stratified cross-validation.

For k selection is based on F1 scores for each model. TO attain the F1 scores for a version of the model, we use out-of-fold predicted probabilities via `cross_val_predict` and choose a decision threshold that maximizes F1 on the training folds (using a small grid of thresholds). This explicitly optimizes for F1 due to class imbalance.

Generalization Controls We rely on stratified cross-validation, feature scaling, and a held-out test set for final evaluation to mitigate overfitting and provide an unbiased estimate of performance.

4 Results

Cross-Validation Summaries

All three tasks used 5-fold stratified cross-validation with F1-score maximization and threshold tuning on predicted probabilities. Standing water selected k=7 with Euclidean distance and threshold=0.35. Weed clusters and nutrient deficiency both selected k=20 with Manhattan distance and threshold=0.29. Distance weighting consistently outperformed uniform weighting across all tasks.

Test Set Performance

Table 1 presents final test set performance for the best configurations identified through cross-validation. All three models use distance-weighted k-NN with Manhattan distance metric and threshold=0.29, except standing water which uses Euclidean distance with threshold=0.35.

Table 1: Test Set Performance of Best k-NN Configurations

Task	k	**Accuracy**	**Precision**	**Recall**	**F1**
Standing Water	7	0.9102	0.7991	0.8551	0.8262
Weed Clusters	20	0.6602	0.3873	0.6178	0.4762
Nutrient Deficiency	20	0.7291	0.4718	0.6980	0.5630

Note: All metrics are from held-out test sets (20% of data). Test set sizes: Standing water (857 samples), Weed clusters (4,753 samples), Nutrient deficiency (6,423 samples). Confusion matrices show: Standing water (TN=597, FP=46, FN=31, TP=183); Weed clusters (TN=2,404, FP=1,161, FN=454, TP=734); Nutrient deficiency (TN=3,562, FP=1,255, FN=485, TP=1,121).

Discussion

The results reveal substantial performance variation across detection tasks. Standing water achieves the strongest performance (CV F1=0.85) with a small neighborhood (k=7) and Euclidean distance, suggesting that water's distinct NIR spectral signature enables effective local classification. The Euclidean metric's success indicates that smooth spectral gradients characterize water presence.

Weed cluster detection proves most challenging (CV F1=0.47), requiring a larger neighborhood (k=20) and Manhattan distance. The lower performance reflects inherent task difficulty: weeds exhibit variable spectral responses and may resemble surrounding vegetation in NIR imagery. The larger k suggests that aggregating over more neighbors helps overcome this variability.

Nutrient deficiency detection (test F1=0.56) falls between the other tasks in difficulty. The model achieves reasonable recall (0.70) but lower precision (0.47), indicating it successfully identifies most deficiency cases but produces notable false positives. This trade-off reflects the optimized threshold (0.29), which prioritizes recall over precision for this imbalanced dataset (25% positive class).

Across all tasks, distance weighting consistently outperformed uniform weighting, prioritizing closer neighbors. Threshold optimization proved essential, with optimal thresholds (0.29–0.35) differing substantially from the default 0.5. The consistent use of k=20 for weeds and nutrients versus k=7 for water suggests that more distinctive features (water) benefit from local neighborhoods, while subtle features require broader context. These findings underscore the importance of careful hyperparameter selection and probability calibration when applying classical ML to agricultural remote sensing.

5 Broader Impacts

Agricultural Applications

Automated detection of standing water has significant positive impacts for agriculture:

- **Irrigation optimization**: Identifying areas with excess water helps farmers adjust irrigation schedules, conserving water resources and reducing costs.
- **Flood damage assessment**: Rapid identification of flooded fields enables timely intervention and insurance claims processing.
- **Disease prevention**: Standing water promotes root rot and fungal diseases; early detection allows preventive measures.
- **Yield prediction**: Water stress indicators help forecast crop yields and optimize harvest timing.

Data Collection Considerations

The manner of data collection introduces several considerations:

- **Geographic bias**: If training data predominantly comes from specific regions, models may not generalize to different climates, soil types, or farming practices.
- **Seasonal bias**: Images collected during specific seasons may miss important variations in water appearance across growing cycles.
- **Sensor characteristics**: NIR sensors have different spectral responses; models trained on one sensor type may require recalibration for others.
- **Labeling accuracy**: Human-annotated labels may contain errors, especially for ambiguous cases like mud versus standing water.

Societal Considerations

Broader deployment of automated agricultural monitoring raises important questions:

Positive impacts:

- Democratization of precision agriculture tools for small-scale farmers
- Reduced chemical use through targeted interventions
- Enhanced food security through improved crop management
- Environmental conservation through water and resource optimization

Potential concerns:

- **Privacy**: Aerial monitoring of private farmland raises surveillance concerns, particularly if systems can identify individual farmers or farming practices.
- **Economic displacement**: Automation may reduce need for human agricultural scouts and field inspectors.
- **Digital divide**: Advanced monitoring systems may only be accessible to well-resourced farms, potentially widening inequality in agricultural productivity.
- **Over-reliance on technology**: Farmers may lose traditional knowledge and observational skills if they depend entirely on automated systems.
- **Misclassification consequences**: False negatives (missed water) could lead to crop loss; false positives might trigger unnecessary interventions and costs.

As these technologies mature, it is essential to ensure equitable access, maintain farmer autonomy in decision-making, and establish clear guidelines around data ownership and privacy (**?**).

6 Conclusions

This work demonstrates that classical computer vision and k-NN can provide strong, interpretable baselines for multiple farmland conditions—standing water, weed clusters, and nutrient deficiency—in NIR aerial imagery. Through task-tailored feature engineering, appropriate normalization, and careful cross-validation (with threshold tuning on imbalanced tasks), we achieve competitive performance without deep learning.

Key contributions include:

- Task-specific feature pipelines: high-dimensional pixel+histogram+stats for water; compact CLAHE-based descriptors for weeds and nutrients
- Systematic k-NN tuning across k, distance metrics, and weighting, with F1-oriented threshold selection for imbalanced settings
- Reproducible end-to-end notebooks for all three tasks to regenerate metrics and figures

Related Work

The Agriculture-Vision Challenge has attracted significant research attention. The 2021 challenge winners employed deep learning architectures, particularly variants of U-Net and DeepLabV3+, achieving mean Intersection over Union (mIoU) scores above 0.60 for semantic segmentation tasks. (Chiu et al. 2020)

Our approach differs fundamentally: we focus on binary image-level classification rather than pixel-level segmentation and employ classical machine learning methods instead of deep learning. While results are not directly comparable, our pipelines demonstrate that well-designed classical approaches can effectively identify the presence of water features and other conditions when appropriate preprocessing, feature engineering, and local feature analysis are applied.

Before the deep learning era, classical computer vision methods for water detection and agricultural monitoring relied heavily on spectral indices (e.g., Normalized Difference Water Index), texture analysis, and local features such as SIFT and SURF, often combined with ensemble classifiers. Local features capture low-level descriptions of keypoints—interest points in an image that are invariant to scale and orientation—and provide robust representations of structures such as edges, corners, and small patterns (Amato and Falchi 2010). Our methodology incorporates histogram equalization, multi-scale descriptors, and local feature-inspired statistics, aligning with these established techniques while adapting them to the unique characteristics of the Agriculture-Vision dataset.

Future Work

Future work could explore additional local and texture-based feature types, such as SIFT, SURF, and edge descriptors, to capture fine-grained variations in crop and environmental conditions. Further improvements could include advanced class-imbalance handling, multi-label classification covering all Agriculture-Vision conditions, and integration of these local features with lightweight machine learning models to enhance both accuracy and interpretability.

7 Contributions

Christian Rutherford conceived and designed the initial models and developed the foundational modeling framework. Jackson McDonald carried out feature engineering and conducted hyperparameter optimization to enhance model performance. Both authors contributed equally to drafting, revising, and finalizing the paper.

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