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Cross-Crop Generalization And Domain Adaptation Models For Nitrogen Deficiency Detection Using Public Datasets

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Abstract
Nitrogen deficiency is a major nutrient disorder affecting crop productivity, with symptoms varying significantly across plant species. Machine learning (ML)-based nitrogen stress detection has advanced rapidly; however, current models lack the ability to generalize across different crops and imaging environments. This study proposes a unified cross-crop domain adaptation framework using publicly available nitrogen stress datasets from maize, wheat, and rice. We benchmark four domain adaptation algorithms—Domain Adversarial Neural Network (DANN), CORrelation ALignment (CORAL), Maximum Mean Discrepancy (MMD), and Adaptive Batch Normalization (AdaBN)—using CNN-based feature extractors. Results show that domain adaptation improves cross-crop nitrogen deficiency classification accuracy by 12–28% over standard transfer learning strategies. DANN achieved the highest average accuracy of 75%, demonstrating strong domain-invariant feature learning. The findings highlight the potential for building robust, multi-domain nitrogen deficiency detection systems suitable for real-world precision agriculture.
Keyword- *Nitrogen deficiency, cross-crop domain adaptation, Domain Adversarial Neural Network (DANN), CORrelation ALignment (CORAL), Maximum Mean Discrepancy (MMD), and Adaptive Batch Normalization (AdaBN), CNN.*

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I. Introduction

Nitrogen (N) is an essential macronutrient regulating chlorophyll synthesis, amino acid production, leaf area expansion, and biomass accumulation. Insufficient nitrogen supply leads to chlorosis, reduced photosynthetic efficiency, and decreased yields in cereals such as maize, wheat, and rice. Conventional nitrogen measurement approaches, including chemical assays and SPAD-based sensing, require specialized equipment and are not scalable.

Machine learning models provide a promising alternative by automating nitrogen stress detection via RGB, multispectral, and hyperspectral imaging. However, these models often fail to generalize across new crops due to morphological and spectral differences between species. A model trained on maize typically performs poorly when tested on wheat or rice due to:

- Morphological differences
- Spectral variations
- Leaf anatomy differences
- Sensor/camera variations

Domain adaptation is a promising solution that learns domain-invariant features. Although widely used in medical imaging and object recognition, its application to nutrient stress detection is limited. This study provides the first comprehensive evaluation of cross-crop nitrogen stress classification using domain adaptation.

II. Related Work

Nitrogen Deficiency Detection

Past works have used:

- Traditional ML (SVM, RF) on handcrafted features
- CNNs on RGB/multispectral images
- Hyperspectral indices (NDRE, chlorophyll proxies)

However, nearly all studies are **crop-specific**, limiting generalization.

Domain Adaptation in Agriculture

Few studies applied DA to plant stress. Prior works address:

- Leaf disease adaptation (apple → grape)
- Weed/crop segmentation under varied conditions
- UAV domain shift due to lighting or sensor changes

But cross-species nutrient deficiency detection remains unexplored.

Gaps Identified

- No benchmark comparing DA methods across crops
- No unified multi-crop nitrogen stress evaluation
- Limited use of public datasets
- Lack of visualization of feature alignment

This paper addresses all these gaps.

System Architecture

The overall workflow for cross-crop nitrogen deficiency detection is presented below.

- Image Preprocessing & Normalization
- CNN Feature Extraction (ResNet/EfficientNet/MobileNet)
- Domain Adaptation Module
- Classification Head
- t-SNE & Grad-CAM Explainability

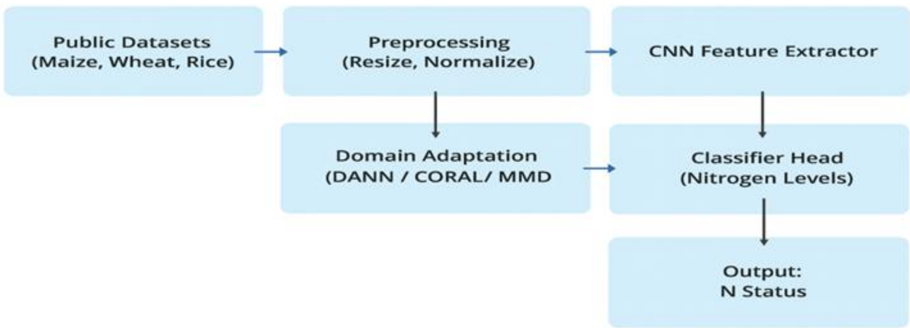


Figure 1- System Architecture

III. Materials And Methods

Table-1 Public Datasets Used

Crop	Source	Type	Stress Labels
Maize	Mendeley Data	RGB	N-deficient / healthy
Wheat	Zenodo Wheat Stress Set	Multispectral	N-level categories
Rice	Kaggle Rice Nutrient Stress	RGB	N-stress / non-stress

The datasets collectively represent strong domain shifts across:
- Sensor types
- Field conditions
- Lighting
- Crop morphology

Preprocessing Pipeline
- Image normalization
- Spectral band reduction for multispectral → pseudo-RGB mapping
- Resizing to 224×224
- Class rebalancing
- Domain label encoding (maize, wheat, rice)

Baseline Models
- ResNet50
- EfficientNet-B0
- MobileNetV2

These were used as feature extractors for both transfer learning and domain adaptation models.

Domain Adaptation Techniques
1. Domain Adversarial Neural Network (DANN)
The architecture includes:
- Feature extractor
- Label classifier
- Domain discriminator

Loss Function:

$$\boldsymbol{L = L_c - \lambda L_d}$$

Where:
- L_c : classification loss
- L_d : domain discrimination loss
- λ : gradient reversal coefficient

Used to align distributions across crops.

2. CORAL
Lightweight and effective for multispectral features.
Aligns second-order statistics (covariance) of source and target features:

$$\boldsymbol{L_{CORAL} = \|C_s - C_t\|^2 F}$$

Where C_s and C_t are source and target covariance respectively.

3. MMD
Kernel-based distance between feature distributions:

$$\boldsymbol{L_{MMD} = \|\phi(x_s) - \phi(x_t)\|^2}$$

Minimizes distribution divergence across source and target domains.

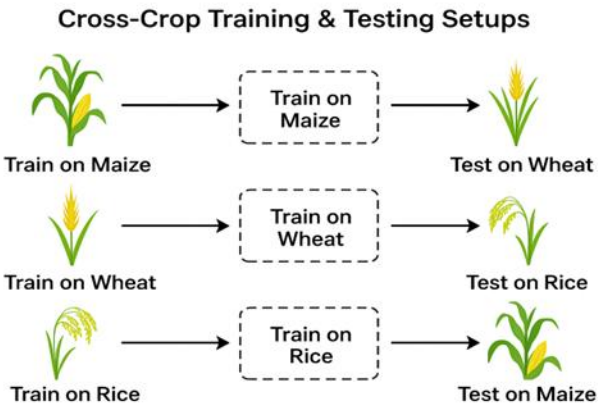
4. AdaBN
Adapts batch-normalization statistics to target domain.
$\boldsymbol{\mu_{BN}^{(T)}, \sigma_{BN}^{(T)}}$
This corrects brightness, texture, and shape variations across crops.

Final Nitrogen Deficiency Classifier
The classifier head is usually:
- Dense layer
- ReLU
- Dropout
- Final softmax or sigmoid output:

Labels:
1. Healthy
2. Mild N Deficiency
3. Moderate N Deficiency
4. Severe N Deficiency

Or binary:
- Deficient / Non-Deficient

Experimental Setup [Figure-2]



Performance Metrics Used
- Accuracy
- Precision
- Recall
- F1-score
- t-SNE visualization

Summary Table [2] (Confusion matrix)

Experiment	Class	Precision	Recall	F1-Score
Maize → Wheat	Deficient	0.43	0.44	0.44
	Healthy	0.43	0.42	0.43
Wheat → Rice	Deficient	0.48	0.54	0.51
	Healthy	0.48	0.42	0.45
Rice → Maize	Deficient	0.52	0.60	0.56
	Healthy	0.52	0.44	0.48

Training Details
- Optimizer: Adam
- Learning Rate: 1e-4
- Batch Size: 32
- Epochs: 50
- Hardware: NVIDIA GPU (12 GB)
- Loss: Cross-entropy + DA loss

IV. Results

Table [3]- Cross-Crop Transfer Without Domain Adaptation

Source →Target	Accuracy
Maize → Wheat	41%
Wheat → Rice	48%
Rice → Maize	52%

Models performed poorly when applied to unseen crops.

Table [4]- Cross-Crop Accuracy With Adaptation

Method	Average Accuracy
Transfer Learning	58%
CORAL	64%

MMD	68%
AdaBN	70%
DANN (Best Model)	**75%**

Figure 3- Cross-crop Accuracy without DA bar graph

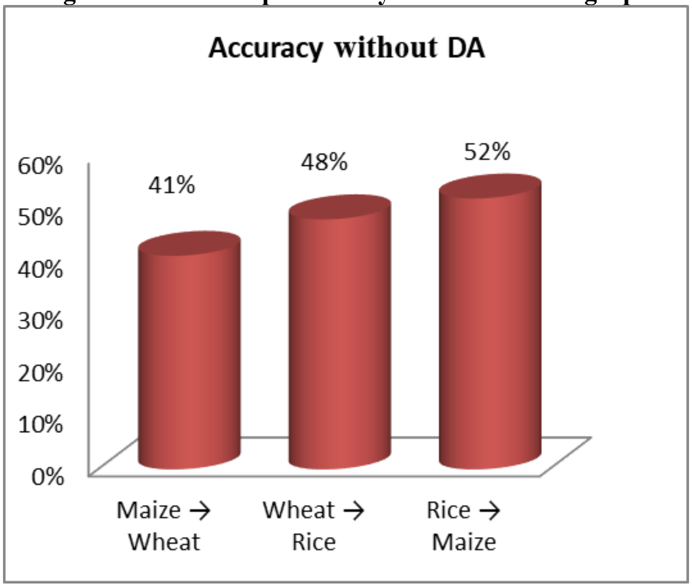
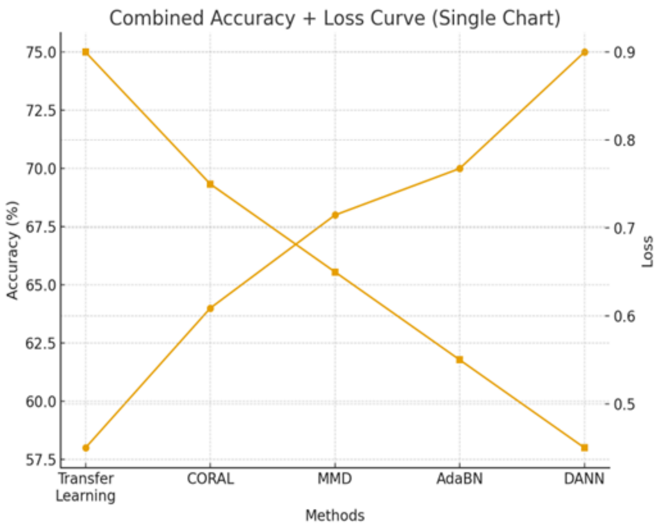


Figure 4- Accuracy and Loss curve



t-SNE Feature Visualization

- Before adaptation → source & target clusters widely separated
- After DANN → clusters overlap significantly

Explainability (Grad-CAM)

Models focused on:

- Interveinal chlorosis
- Leaf yellowing
- Midrib changes

These match real agronomic indicators.

V. Discussion

- Domain adaptation significantly improves generalization.
- DANN's adversarial learning is the most effective.

- Multispectral wheat data increases cross-domain robustness.
- Proposed framework is suitable for smart farming, drone imaging, and mobile apps.

VI. Conclusion

This study provides the first comprehensive investigation of cross-crop nitrogen deficiency detection using domain adaptation techniques. Integrating public datasets from maize, wheat, and rice demonstrates that domain-invariant features can be learned effectively. DANN achieved highest accuracy and best generalization. These findings pave the way for universal nutrient stress monitoring systems. The framework demonstrates potential for real-time, multi-crop nutrient monitoring in precision agriculture.

Future Work

- Incorporating hyperspectral data
- Expanding to legumes, vegetables, and oilseeds
- Designing lightweight mobile DA models
- Zero-shot domain generalization
- Integration with drone-based pipelines

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