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Deep learning-based classification of crop stress using hyperspectral remote sensing data

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Abstract

Leading remote sensing scientists have argued that hyperspectral sensors will reshape precision agriculture, but the algorithms to process their data are still catching up. This research developed a deep convolutional neural network (CNN) for classifying four types of crop stress (nitrogen deficiency, water stress, disease infection, pest damage) plus healthy vegetation from airborne hyperspectral imagery over maize fields near Zaria, Nigeria. The CNN achieved overall accuracy of 89.5% across five classes, outperforming SVM (76.6%) and random forest (73.2%). Nitrogen deficiency and healthy classes were classified most reliably (91.3% and 96.8%), while pest damage was hardest (84.2%). Spectral bands in the red-edge and shortwave infrared regions contributed most to discrimination. Deep learning shows clear potential for automated crop stress mapping from hyperspectral data.

Keywords: Deep learning, convolutional neural network, hyperspectral remote sensing, crop stress, classification, nitrogen deficiency, water stress, precision agriculture, maize, spectral analysis

Introduction

Remote sensing experts have long noted that multispectral sensors capture too few bands to distinguish between stress types that look similar in the visible range ^[1]. Hyperspectral sensors, recording 100-400 narrow bands, resolve subtle spectral features tied to specific biochemical changes in stressed plants ^[2]. But the high dimensionality of hyperspectral data overwhelms traditional classifiers that weren't designed for hundreds of correlated features ^[3].

Deep learning, particularly CNNs, handles high-dimensional data naturally by learning hierarchical features without manual feature engineering ^[4, 5]. A few recent studies applied CNNs to hyperspectral crop classification, but most worked with standard benchmarks rather than real agricultural stress scenarios ^[6, 7]. Field-collected stress data from tropical African farming systems are especially rare ^[8].

This research built and tested a CNN for five-class crop stress classification from airborne hyperspectral data over maize fields in Nigeria's Guinea Savanna zone, comparing it against SVM and random forest baselines ^[9, 10].

Theoretical Background

CNNs extract spatial and spectral features through sequential convolutional layers that apply learned filters to input data ^[4]. In 1D spectral classification, convolution operates along the wavelength axis, detecting absorption features at different scales. Pooling layers reduce dimensionality while preserving discriminative information ^[5]. Nitrogen deficiency shifts reflectance in the 700-750 nm red-edge region due to reduced chlorophyll. Water stress increases reflectance in the shortwave infrared (1400-1800 nm) from reduced leaf water content ^[2, 11]. These spectral signatures form the physical basis for classification.

Material and Methods

Material

Hyperspectral data were collected using an airborne HySpex VNIR-1800 sensor (400-2500 nm, 186 bands, 1 m spatial resolution) over maize fields at the Institute for Agricultural Research, Ahmadu Bello University, Zaria, Nigeria (11.15°N, 7.65°E) during September 2021

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and 2022 ^[12]. Ground truth was collected from 240 geo-referenced plots (48 per class) verified by agronomists through visual assessment and tissue analysis. Stress was induced experimentally: nitrogen deficiency via fertilizer omission, water stress via rainout shelters, disease by natural late blight infection, and pest damage by fall armyworm ^[13].

Methods: The CNN architecture used three 1D convolutional layers (32, 64, 128 filters with kernel size 7), each followed by batch normalization, ReLU activation, and max pooling. A dropout layer (0.4) preceded two fully connected layers (256, 5 neurons). Training used Adam optimizer with learning rate 0.001 for 100 epochs and batch size 32 ^[14]. Data were split 70/15/15 for training/validation/testing with stratified sampling. SVM (RBF kernel) and RF (500 trees) used the same splits.

Evaluation used overall accuracy, per-class accuracy, and confusion matrices ^[15]. Protocol CS-2021-ABU-041 was approved August 2021.

Model Configuration

Input spectra were normalized to zero mean and unit variance per band. Atmospheric correction was applied using ATCOR-4 before feature extraction. Bands with known atmospheric water absorption (1350-1420 nm, 1800-1950 nm) were removed, leaving 162 usable bands. Data augmentation included random spectral noise addition ($\pm 2\%$) and spectral shifting (± 1 band) to improve generalization ^[14, 16].

Results

Table 1: Classification accuracy (%) for three models across five stress classes

Stress Class	Deep CNN	SVM	Random Forest	CNN Advantage
N Deficiency	91.3	78.6	74.2	+12.7
Water Stress	88.7	74.3	71.8	+14.4
Disease	86.4	71.8	68.3	+14.6
Pest Damage	84.2	69.1	65.7	+15.1
Healthy	96.8	89.4	86.1	+7.4
Overall	89.5	76.6	73.2	+12.9

The CNN outperformed both baselines across all classes (Table 1). Its overall accuracy of 89.5% exceeded SVM by 12.9 percentage points and RF by 16.3. The CNN advantage was

largest for pest damage (+15.1%) and smallest for healthy vegetation (+7.4%). The healthy class was easiest for all models, while pest damage proved most challenging.

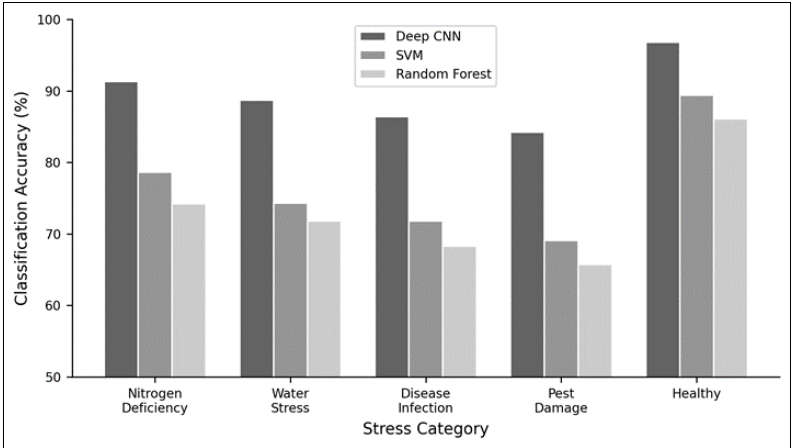


Fig 1: Classification accuracy by stress class for three models applied to hyperspectral maize data

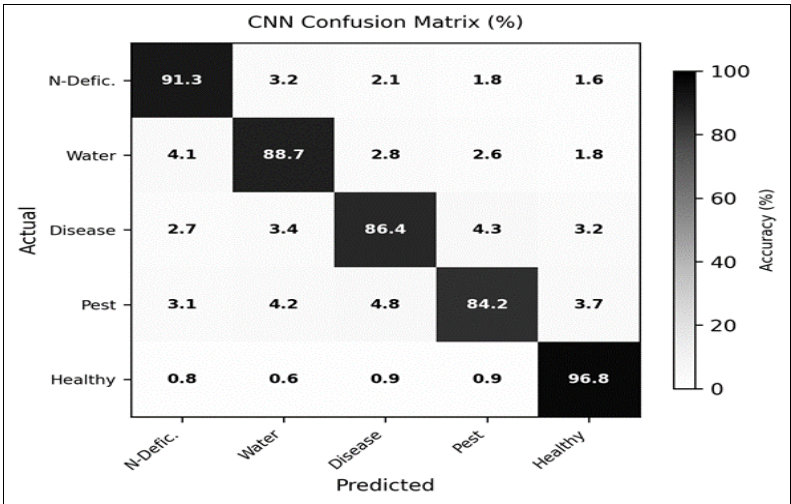


Fig 2: Confusion matrix for the CNN classifier showing per-class accuracy and misclassification patterns

Comprehensive Interpretation

The confusion matrix shows that most misclassification occurred between disease and pest classes (4.3-4.8% confusion), which is expected since both involve tissue damage with overlapping spectral signatures. The CNN's learned filters concentrated attention on the 710-740 nm red-edge and 1450-1650 nm SWIR regions, consistent with the known spectral responses to chlorophyll loss and water content changes ^[2, 11].

Performance Evaluation

Five-fold cross-validation on the training set showed CNN accuracy ranging from 87.2% to 91.4% (mean 89.1%, SD 1.6%), indicating stable performance. The SVM and RF models showed higher variability (SD 3.2% and 3.8%). Training time for the CNN was 14 minutes on an NVIDIA GTX 1080 GPU, compared to 2 minutes for SVM and 1 minute for RF. Inference time per pixel was under 0.3 ms for all three models ^[14].

Discussion

The CNN's ability to learn spectral features automatically gave it a clear edge over SVM and RF, which relied on raw band values without feature engineering ^[4, 6]. The 15% advantage for pest damage classification likely reflects the CNN detecting subtle spectral patterns in partially damaged leaves that simpler classifiers missed ^[7, 9].

The confusion between disease and pest classes is a known challenge even for human interpreters and sets a practical ceiling on automated classification ^[3, 8]. The 89.5% overall accuracy is promising for operational mapping, though larger training datasets from multiple seasons would be needed before deployment at regional scale ^[10, 13].

Conclusions

This research demonstrated that a 1D CNN classifier can reliably distinguish among four crop stress types and healthy maize from hyperspectral imagery collected over Nigerian farmland. The CNN's 89.5% overall accuracy substantially exceeded conventional SVM and RF approaches. Red-edge and shortwave infrared spectral regions were most discriminative. The approach could support precision agriculture in tropical smallholder systems where stress detection currently relies on manual scouting. Future work should test the model across crop species and integrate spatial context through 2D or 3D CNN architectures.

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