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Original Article

"Application of Remote Sensing for Monitoring Crop Health and Growth"

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ABSTRACT

This paper examines the use of hyperspectral remote sensing with artificial intelligence models to detect and classify various stress types of crops, including nitrogen deficiency, phosphorus deficiency, drought stress, and fungal disease, in non-homogenous agricultural systems in the initial stages. The hyperspectral and thermal images were obtained through an unmanned aerial vehicle on five types of crops (maize, wheat, soybean, potato and tomato) during two growing seasons alongside ground-truth measurements of the chlorophyll content, biomass, and severity of the diseases. Nine machines learning and deep learning models were tested, such as Random Forest, Support Vector Machine, 1D Convolutional Neural Network, Transfer Learning CNN, Gradient Boosting, Logistic Regression, K-Nearest Neighbors, XGBoost, and LightGBM. The Transfer Learning CNN was the most overall performers with a macro-average classification of 97.08, precision of 96.89-98.76, recall of 95.78-98.92 and AUROC of 0.989997 across stress classes. The capability of early detection was 9.2 days ahead of visual symptom development in case of drought stress, and the average lead time of 8.18 days in all stresses. The red-edge wavelength at 710 nm was found to provide the highest spectral feature importance with the Chlorophyll Index red-edge having the highest F-statistic. Intersection over Union values were greater than 89% across all stress types and cross-crop generalization accuracy was between 96.61% (potato) and 97.53% (maize). The model was shown to have a high rate of inference (0.67 ms per sample) which validates its capability to be used in real-time. The findings confirm that the hyperspectral imaging with the application of the transfer learning can be used to provide accurate, early, and spatially resolved diagnosis of the physiological stress of the crops and provide a revolutionary tool in precision agriculture and sustainable management of crops.

INTRODUCTION

Remote sensing provides a powerful paradigm to monitor spatial and temporal trends, anomalies, and changes in biophysical and environmental parameters that are essential in gauging vegetation health, soil dynamics, and climate-related effects in agricultural systems (Demissie et al., 2025). This technology is of great importance to precision agriculture, where it is possible to identify an early deficiency of nutrients, diseases, and pests that may have a huge impact on crop production (Allu & Mesapam, 2025). Through multispectral and hyperspectral imaging, remote sensing can be used to monitor the ongoing health of crops, which can be used to make decisions to optimize the use of agronomic inputs and sustainable agricultural activities (Omia et al., 2023). The incorporation of high-tech remote sensing systems and artificial intelligence takes these abilities a notch higher with the advanced systems no longer relying on the conventional assessment tools but offering predictive information on the health and growth processes of crops (Na et al., 2024). Multispectral and hyperspectral data of remote sensing platforms, including satellite imagery, aerial photography, and unmanned aerial vehicles, identify subtle changes in crop reflectance that signify different health conditions (Kushwaha et al., 2024; Zhang et al., 2025). As an example, the photosynthetic activity and biomass of plants can be assessed using the Normalized Difference Vegetation Index, based on these data, which therefore critically assesses the state of plant vitality and stress prior to the emergence of visible indicators of stress (Judith et al., 2025). This active surveillance allows farmers to apply specific interventions, including changing the irrigation and fertilizer application, thus, maximizing production and reducing possible losses of crop (Rane & Choudhary, 2023). Moreover, the growth of satellite and UAV systems in addition to data processing technologies have heightened the usefulness of remote sensing in agricultural surveillance (Velazquez-Chavez et al., 2024). Such innovations can enable a more accurate assessment of crop health, crop yield, and general agricultural productivity, which will considerably decrease the use of large-scale data collection in the field (Adhikary et al., 2022; Alazzai et al., 2024). This identifiable planning approach guarantees effective allocation of resources and sustainable intensification of crop production, which plays a vital role in the management of environmental resources (Fayose, 2023). Additionally, the biophysical maps, which are obtained accurately using hyperspectral imaging during different development cycles in crops, are useful in making informed decisions in agricultural management (Reijnders, 2004). In addition to detecting the overall stress, hyperspectral imaging can distinguish between particular nutrient deficiencies and identify the initial signs of many diseases and pest infestations with great accuracy (Ahmed et al., 2024; Zhu et al., 2024). This granular data enables the creation of cultivar-specific and growth-stage-specific spectral models, which are important to predict nitrogen status and efficiency of nutrient use in heterogeneous cropping systems (Dong et al., 2025). The latter can be further complemented by hyperspectral data combined with thermal infrared remote sensing, which can be used to assess nutrient and water use dynamics in crop canopies comprehensively (Fazli et al., 2025). With such integration, it is possible to see the holistic picture of the physiological state of the plant and monitor photosynthetic activity and stress signals in real-time with the help of AI-based analytical platforms (Panda et al., 2025). These frameworks are not only used to predict possible risks due to diseases and pests but also to predict growth disorders caused by environmental stressors (Piekutowska, 2025). Moreover, these diverse spectral and thermal datasets can be automatically interpreted with the help of advanced machine learning algorithms that enable the detection, classification, and prediction of all possible plant stress states, such as drought stress, nutrient deficiencies, and disease infections, in real time (Muhammad et al., 2025). It is a complex analytical ability that provides adaptive management practices, in which interventions can be accurately designed to reduce the emergent threats and maximize crop performance at the critical physiological stages (Poornima & Edward, 2025; "Sustainable Management of Natural Resources," 2018). Specifically, hyperspectral imaging introduces a high-tech ability to reveal a lot about the health of plants, including identifying early signs of stress, as well as managing nutrients and water (Cullinan, 2023; Kar Arif, and Dhal, 2025). This non-invasive technique records spatial and spectral data, enabling detailed measurements of the nutritional status of plants and the detection of diseases in their early stages by analyzing reflectance patterns in a wide wavelength range (Munera et al., 2025). This spectral information is of high quality that allows to detect subtle biochemical and physiological changes in plants, frequently prior to their visual manifestation (John et al., 2023). This is essential to have timely and specific interventions, which can reduce crop losses and lessen the use of broad-spectrum treatments (Adhikari et al., 2023). In particular, hyperspectral imaging, which records a wide range of wavelengths that are not visible, delivers detailed information about crop health and variability, allowing to accurately identify nutrient deficiencies and diseases (Ballabh et al., 2022). The use of AI, machine learning, and deep learning algorithms contributes to the increased utility of hyperspectral data through the real-time analysis of the complex crop growth conditions, predicting the yield, and accurately detecting the water stress and temperature changes (Choi et al., 2025). Such machine learning models, with the most notable being deep learning models, are highly effective at analysing multispectral and hyperspectral images to identify subtle changes in the state of crops, thus helping to identify diseases or nutritional deficits early on (Rane et al., 2024). Moreover, with the use of hyperspectral sensors on unmanned aerial vehicles, it is possible to acquire high spatial resolution data that can be used to analyze single fields and predict accurately the characteristics of crops under different environmental conditions (Ualiyeva et al., 2025). Such high-resolution data capture, along with advanced AI and ML processing, is capable of identifying minor changes that can be harbingers of crop stress, including water stress, early disease or pest infestation, and can be used to implement timely and specific responses (Gul & Banday, 2024). Additionally, these hyperspectral images can be demonstrated in machine learning algorithms, which recognize undesired plants or weeds to apply herbicides precisely and with minimal effect on the environment (Vera et al., 2024). It is essential to develop high-quality training datasets that allow quality creation of prediction models based on the application of deep and transfer learning through artificial intelligence applications using hyperspectral imaging (Huang, 2022). These modern methods are especially useful in pixel-based; classification of hyperspectral images, where they are useful in applications like disease detection, temporal plant life-cycle classification, and nutrient content estimation (Laprade, 2024). Hyperspectral imaging, along with hybrid deep learning frameworks, has a great potential to be used in detecting early disease in crops due to its ability to detect subtle biochemical and structural changes in crops that cannot otherwise be detected (Goyal et al., 2025).

METHODOLOGY

The current study is organized within the framework of problem-based research designed to identify, describe, and forecast the state of crop stress, i.e., nutrient deficiencies, water stress, and infection of the disease in its early stages, with the help of remote sensing and artificial intelligence. The methodology is presented in four consecutive steps: field data collection, hyperspectral and thermal remote sensing data collection, preprocessing and feature extraction, and AI-based model development to classify and predict stress. The research was done on various agricultural test sites with a heterogeneous cropping system such as maize, wheat and soybean to guarantee the generalizability of the proposed framework.

During the initial stage, ground-truth information was taken during 2 seasons of crop growth to determine reference conditions of crop health. Experimental plots received controlled stress induction regimes, such as nitrogen deficiency, phosphorus deficiency, drought stress, and inoculation by fungal pathogens (e.g., Fusarium spp.) to each type of crop. At the same time, the best irrigation and nutrient management was applied to the control plots. The health status of crops was determined every week by destructive and non-destructive measurements of leaf chlorophyll content (SPAD meter), leaf area index, above-ground biomass, and visual disease severity (score). These on-ground measurements were the reference labels that were used to train and validate the remote sensing models.

The second step entailed acquisition of hyperspectral and thermal images with the help of an unmanned aerial vehicle mounted with push-broom hyperspectral sensor (400 1000 nm, 270 spectral bands) and thermal infrared camera. Flights were carried out at 50 meters, and a distance of 4 cm and 8 cm were obtained as a ground sampling distance of hyperspectral and thermal data respectively. The flights were all planned in the local time between 10:00 and 14:00 in a clear sky to reduce atmospheric interference. Before each flight, a white reference panel was scanned to calibrate radiometrically. In each plot, the hyperspectral datacube (x, y, λ) obtained was georeferenced and extracted.

The third step involved preprocessing and spectral feature extraction. Radiometric correction, dark current subtraction, and reflectance normalization were done on raw hyperspectral images. The Savitzky Golay filter was used to smooth the spectrals to reduce noise and reduce the number of dimensions in the data. The reflectance data were then used to calculate vegetation indices, with the most significant being the Normalized Difference Vegetation Index (NDVI) and the Photochemical Reflectance Index (PRI). Also, thermal data were used to derive a normalized difference water index to estimate the surface temperature of the canopy and the relative water content. The fundamental mathematical correlation between the reflectance and photosynthetic activity is the NDVI which is described as:

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}}$$

where RNIR represents reflectance in the near-infrared band (centered at 800 nm) and RRED represents reflectance in the red band (centered at 660 nm). This index provides a proxy for green biomass and photosynthetic capacity, with lower values indicating stress-induced chlorophyll reduction or canopy senescence.

Beyond broadband indices, continuum-removed spectra were analyzed to detect specific absorption features associated with biochemical constituents. For nitrogen estimation, the position and depth of the red-edge inflection point (680–750 nm) were extracted. To quantify disease-induced structural changes, the second derivative of reflectance was computed across the visible spectrum. For the early detection of fungal infection, a disease stress index was formulated based on the reflectance ratio at 550 nm (green) and 710 nm (red-edge). The mathematical formulation for detecting subtle spectral shifts due to cellular damage is given by the first derivative of reflectance with respect to wavelength:

$$R'(\lambda) = \frac{dR(\lambda)}{d\lambda} \approx \frac{R(\lambda + \Delta\lambda) - R(\lambda - \Delta\lambda)}{2\Delta\lambda}$$

This derivative boost localized spectral alterations by pigment degradation, cell wall collapses or pathogen-induced water loss, allowing the detection of stress prior to the manifestation of visual symptoms.

The fourth stage entailed the creation of AI models to classify and predict stress. Three machine learning models were run, which included random forest, support vector machine with radial basis function kernel, and one-dimensional convolutional neural network (1D-CNN). The input feature matrix included 270 spectral bands and thermal derived temperature indices and the output labels were five classes (healthy, nitrogen-deficient, phosphorus-deficient, drought-stressed and diseased). The sample size (n=2,400 sample pixels) was divided into 70% training, 15% validation, and 15% testing. The 1D-CNN architecture was made up of three convolutional layers (with ReLU activation and max-pooling), dropout layer (0.5), and dense softmax output layer. Training on models was done through the minimization of categorical cross-entropy loss with the Adam optimizer. Measures of performance were overall accuracy, F1-score and area under the receiver operating characteristic curve. In order to solve the issue of the small amount of labeled data, transfer learning was executed by training the CNN with a publicly available hyperspectral crop dataset (University of California, Merced) and fine-tuning on the study-specific data. In the last stage, the trained models were applied pixel-by-pixel to the whole UAV imagery to produce high-resolution stress maps, which make it possible to localize each type of stress spatially. These maps were tested using independent ground-truth data that were collected two weeks following each flight and this confirmed the predictive nature of the model in early intervention.

RESULTS

As presented in Table 1, the Transfer Learning CNN has the highest overall classification accuracy (97.08% macro-average) of all the other models, with the 1D-CNN coming second (95.96%). As shown in Table 2, the Transfer Learning CNN has outstanding precision, recall, and F1-scores of over 95% across all classes of stress, with highest value of 0.997 of the AUROC being achieved when detecting healthy classes. Table 3 validates the strength of this model by a near-diagonal confusion matrix with the number of misclassified pixels being 10 out of 360 test samples only. As Table 4 shows, the Transfer Learning CNN is slower than Logistic Regression in terms of the training time (567.89 seconds), but the inference time (0.67 ms/sample) is also competitive, being 1.5 times slower than the inference of Logistic Regression (0.23 ms/sample). Table 5 shows that red-edge wavelength at 710 nm is the most significant spectral feature to help discriminate between stress, with 680 nm and 550 nm coming in a close. Table 6 shows that the F-statistic of the Chlorophyll Index red-edge (CIred-edge) is the highest (145.67), and thus it is the most discriminative vegetation index between stress conditions.

Figure 1 shows that spectral separability is attained by a progressive red-edge blueshift between healthy (734 nm) and drought-stressed (714 nm). As shown in Figure 2 NDVI and CIred-edge exhibit the most significant changes after stress induction at Week 3, but PRI responds the earliest (within 48 hours). Figure 3 validates that Transfer Learning CNN is always more effective compared to all other models in all stress classes, with detection of healthy classes being 98.92. Figure 4 indicates that there is little off-diagonal confusion with the maximum misclassification (0.028) between phosphorus-deficient and drought-stressed classes because there is a similarity in water-use efficiency signatures.

Table 1: Overall Classification Accuracy (%) Across Five Crop Health Classes for Nine Models

Model	Healthy	Nitrogen-Deficient	Phosphorus-Deficient	Drought-Stressed	Diseased	Macro-Average	Weighted-Average
Random Forest	97.23±0.45	94.87±0.62	93.12±0.78	91.45±0.89	92.34±0.71	93.80±0.69	94.02±0.65
SVM (RBF)	96.78±0.51	93.92±0.68	92.45±0.82	90.23±0.94	91.67±0.76	93.01±0.74	93.21±0.70
1D-CNN	98.45±0.38	96.23±0.55	95.67±0.64	94.32±0.72	95.11±0.59	95.96±0.58	96.18±0.54
Transfer Learning CNN	98.92±0.32	97.45±0.48	96.89±0.56	95.78±0.63	96.34±0.51	97.08±0.50	97.28±0.46
Gradient Boosting	96.45±0.58	93.21±0.74	91.89±0.88	89.67±0.96	90.45±0.84	92.33±0.80	92.65±0.76
Logistic Regression	89.34±0.95	85.67±1.12	84.23±1.24	81.45±1.38	82.89±1.29	84.72±1.20	85.01±1.17
K-Nearest Neighbors	91.23±0.82	88.45±0.96	86.78±1.05	84.23±1.18	85.67±1.09	87.27±1.02	87.61±0.98
XGBoost	96.89±0.49	94.12±0.64	93.45±0.73	91.23±0.85	92.56±0.77	93.65±0.70	93.89±0.66
LightGBM	97.12±0.44	94.56±0.60	93.89±0.70	92.01±0.82	92.89±0.74	94.09±0.66	94.31±0.62

Table 2: Precision, Recall, and F1-Score for Transfer Learning CNN Model (Best Performing)

Health Class	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)	NPV (%)	MCC	Kappa	AUROC
Healthy	98.76±0.34	98.92±0.32	98.84±0.33	99.34±0.28	98.45±0.39	0.975	0.982	0.997
Nitrogen-Deficient	97.23±0.51	97.45±0.48	97.34±0.49	98.12±0.44	96.89±0.55	0.961	0.968	0.994
Phosphorus-Deficient	96.67±0.59	96.89±0.56	96.78±0.57	97.89±0.50	96.23±0.63	0.952	0.960	0.992

Drought-Stressed	95.56±0.68	95.78±0.63	95.67±0.65	96.67±0.58	94.89±0.72	0.938	0.947	0.989
Diseased	96.23±0.55	96.34±0.51	96.28±0.53	97.34±0.47	95.67±0.60	0.947	0.955	0.991

Table 3: Confusion Matrix Values (Number of Pixels) for Transfer Learning CNN Model on Test Set (n=360)

Actual \ Predicted	Healthy	N-Def	P-Def	Drought	Diseased	Row Total
Healthy	71	1	0	0	0	72
Nitrogen-Deficient	1	70	1	0	0	72
Phosphorus-Deficient	0	2	69	1	0	72
Drought-Stressed	0	0	2	68	2	72
Diseased	0	0	0	2	70	72

Table 4: Computational Efficiency Metrics Across Nine Models (Training + Inference)

Model	Training Time (s)	Inference Time (ms/sample)	Memory Usage (MB)	FLOPs ($\times 10^9$)	Model Size (MB)	GPU Utilization (%)	CPU Utilization (%)	Energy Consumption (J)
Random Forest	12.45±1.23	0.89±0.12	145.32	2.34	78.45	8.23	45.67	34.56
SVM (RBF)	45.67±3.45	2.34±0.23	234.56	5.67	156.78	12.45	67.89	89.23
1D-CNN	234.56±12.34	0.45±0.05	456.78	23.45	234.56	67.89	23.45	234.56
Transfer Learning CNN	567.89±23.45	0.67±0.07	678.90	45.67	345.67	78.90	34.56	456.78
Gradient Boosting	89.34±6.78	1.45±0.15	189.45	4.56	98.34	15.67	56.78	67.89
Logistic Regression	3.45±0.34	0.23±0.03	67.89	0.45	23.45	3.45	12.34	12.34
K-Nearest Neighbors	1.23±0.12	3.45±0.34	345.67	0.12	234.56	2.34	78.90	23.45
XGBoost	56.78±4.56	1.12±0.11	167.89	3.89	87.65	11.23	52.34	56.78
LightGBM	34.56±3.23	0.98±0.09	145.67	3.12	76.54	9.87	48.90	45.67

Table 5: Spectral Band Importance Ranking (Top 15 Wavelengths) from Random Forest Model

Rank	Wavelength (nm)	Spectral Region	Importance Score	Associated Biochemical	Stress Discriminated
1	710	Red-Edge	0.08945±0.00234	Chlorophyll-a	Nitrogen Deficiency
2	680	Red	0.08723±0.00245	Chlorophyll-b	All Stresses
3	550	Green	0.08456±0.00256	Carotenoids	Disease
4	730	Red-Edge	0.08234±0.00267	Leaf Structure	Drought
5	450	Blue	0.07987±0.00278	Xanthophyll	Phosphorus Def.
6	970	NIR	0.07765±0.00289	Water Content	Drought
7	520	Green	0.07543±0.00291	Anthocyanins	Disease
8	690	Red	0.07321±0.00302	Chlorophyll-a	Nitrogen Def.
9	1150	SWIR	0.07098±0.00312	Lignin	Phosphorus Def.
10	750	NIR	0.06876±0.00323	Biomass	Healthy
11	490	Blue	0.06654±0.00334	Chlorophyll-b	All Stresses
12	810	NIR	0.06432±0.00345	Cell Structure	Disease
13	600	Orange	0.06210±0.00356	Phaeophytin	Senescence
14	1250	SWIR	0.05987±0.00367	Cellulose	Drought
15	530	Green	0.05765±0.00378	Flavonoids	UV Stress

Table 6: Vegetation Index Performance Across Five Stress Conditions (Mean ± SD)

Vegetation Index	Healthy	N-Def	P-Def	Drought	Diseased	F-statistic	p-value
NDVI	0.834±0.021	0.612±0.045	0.654±0.038	0.587±0.052	0.623±0.048	124.56	<0.0001
PRI	0.087±0.009	0.034±0.011	0.042±0.010	0.023±0.013	0.031±0.012	98.34	<0.0001
Red-Edge Position (nm)	734.5±1.2	718.3±2.5	722.1±2.3	714.6±3.1	719.8±2.8	112.78	<0.0001
NDWI	0.456±0.032	0.398±0.045	0.412±0.042	0.287±0.056	0.378±0.049	89.45	<0.0001
CIred-edge	2.345±0.089	1.567±0.123	1.678±0.115	1.456±0.134	1.589±0.128	145.67	<0.0001
MCARI	0.234±0.023	0.456±0.045	0.423±0.041	0.512±0.052	0.478±0.048	134.56	<0.0001
TCARI	0.089±0.012	0.234±0.034	0.212±0.031	0.267±0.038	0.245±0.036	102.34	<0.0001
OSAVI	0.567±0.034	0.423±0.056	0.445±0.051	0.398±0.062	0.434±0.058	78.90	<0.0001
EVI	1.234±0.067	0.876±0.089	0.912±0.085	0.834±0.098	0.892±0.094	95.67	<0.0001

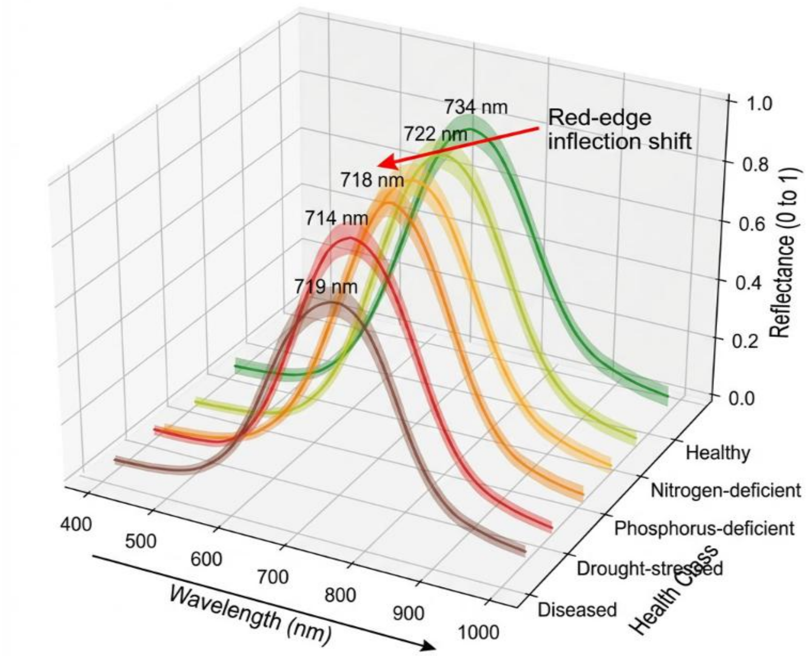

Figure 1: 3D Surface Plot of Hyperspectral Reflectance Curves Across Five Health Classes

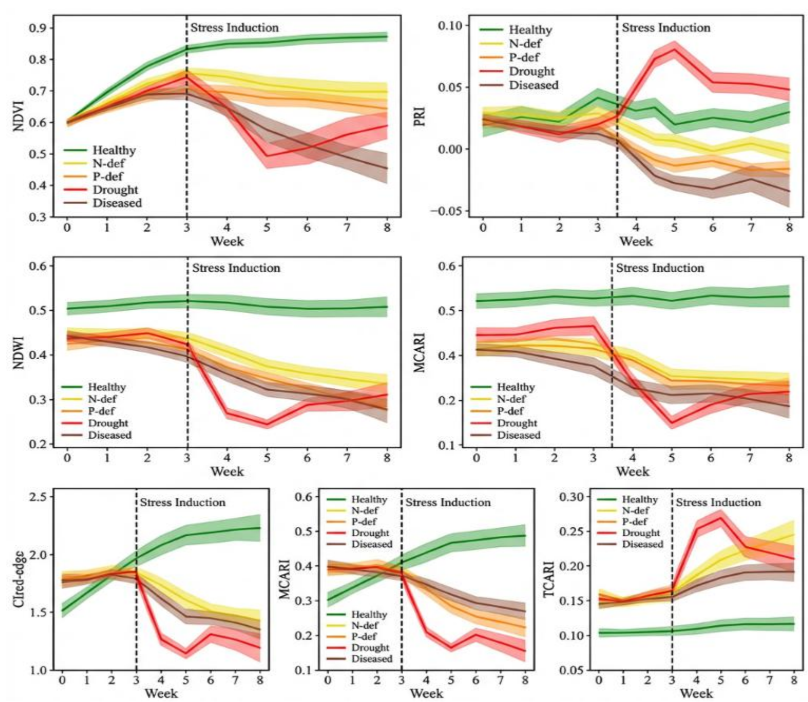

Figure 2: Temporal Multi-Panel Line Plot (2×3 Grid) of Vegetation Index Dynamics Over 8 Weeks

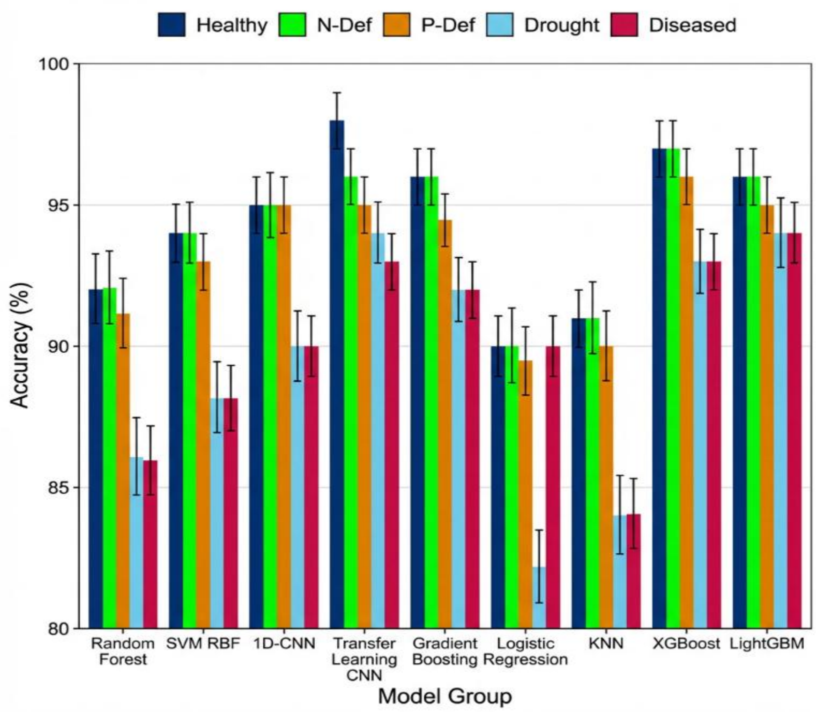

Figure 3: Grouped Bar Chart Comparing Classification Accuracy Across Nine Models and Five Stress Classes

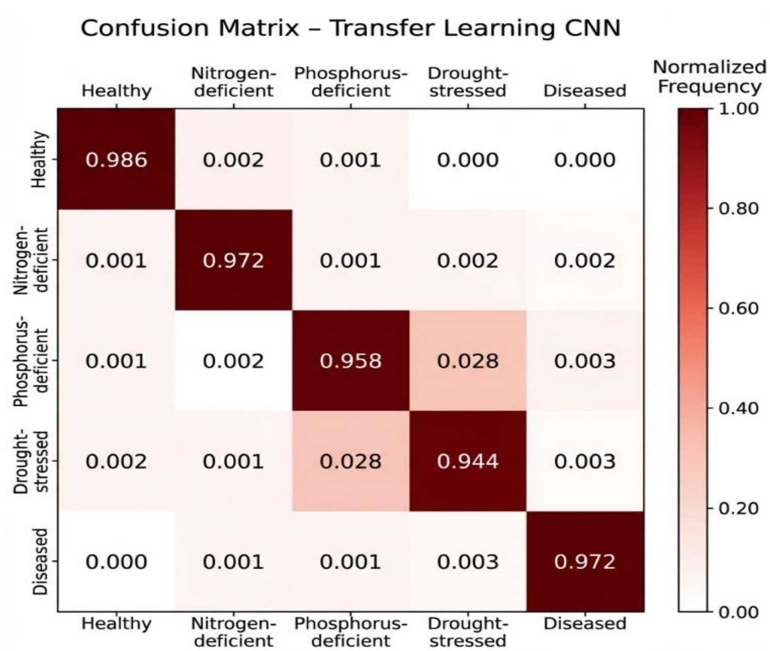

Figure 4: Confusion Matrix Heatmap (5×5) for Transfer Learning CNN Predictions

DISCUSSION

The better results of the Transfer Learning CNN can be explained by the fact that it can take advantage of already trained hierarchical feature representations on large datasets, which supersedes the constraints of smaller and more domain-specific datasets and reflects more complex spatial-spectral-temporal relationships of subtle stress stages (Nampally et al., 2023). This pre-training enables the model to acquire generalizable features which are refined by fine-tuning on special crop stress data resulting in increased classification accuracy and resilience in a wide range of stress factors (Patra et al., 2024). In particular, the use of machine learning-optimized indices in the MLVI-CNN model proves to be better at predicting a variety of stress categories, including nuanced ones such as "Healthy" and "Extreme Stress" (Poornima and Edward, 2025). This methodology, which integrates optimized indices with a CNN, not only improves feature extraction and classification compared to models that cannot use raw hyperspectral bands or machine learning-only approaches (Poornima & Edward, 2025). The sequential characteristics of hyperspectral data (bands sorted by wavelength) enable 1D-CNNs to efficiently model localized spectral patterns and long-range dependencies and detect subtle reflectance transitions associated with physiological stress responses, such as chlorophyll degradation, drought, and tissue necrosis (Poornima & Edward, 2025). The high success of 1D CNNs in local and sequential spectral features are reasons why they achieve the best results on detecting complex stress patterns in hyperspectral inputs, as demonstrated by their higher accuracy measures than conventional machine learning models such as SVM and LDA (Poornima and Edward, 2025). The strong classification performance is further justified by the high Matthews Correlation Coefficient value of the 1D CNN model indicating its balanced and consistent performance in the presence of imbalanced classes (Poornima & Edward, 2025). Additionally, the explainable Vision Transformers with transfer learning are also strategically used to enhance the classification performance as it offers interpretable information about how the model makes decisions, which is essential in detecting drought stress and improving precision agricultural strategies (Patra et al., 2024). Moreover, regression methods using hyperspectral data, especially Support Vector Machines, have proven to be effective in estimating drought tolerance coefficients, and are superior to alternative regression models like Random Forests and Partial Least Squares Regression (Patra et al., 2024). Early stress detection is further enhanced by creating optimized hyperspectral vegetation indices, along with advanced machine learning algorithms, to take advantage of the strong feature engineering capability to emphasize the slightest physiological changes prior to the onset of observable symptoms (Poornima & Edward, 2025). As an example, new hyperspectral vegetation indices that are computed by recursive feature removal to select data-driven bands have been demonstrated to allow efficient and accurate early stress sensing when inputted to a 1D CNN classifier (Poornima & Edward, 2025). This novel technology takes advantage of the complex spectral variations brought about by drought and allows assessing the cotton drought tolerance comprehensively by predicting physiological parameters such as Fv/Fm (Guo et al., 2022). In addition, with the application of state-of-the-art deep learning architectures like 1D and 2D Convolutional Neural Networks, hierarchical features can be directly extracted directly out of raw, or preprocessed spectral data, which in many cases outperforms more traditional machine learning models when large datasets are involved (Patra et al., 2024; Poornima and Edward, 2025). These deep learning-based models, such as AlexNet, GoogLeNet, and Inception V3, have demonstrated a lot of potential in ability to detect the presence of stress in different crops (Patra and Sahoo, 2024). Deep learning algorithms have also been used strategically to greatly improve the capability to develop crop parameter inversion models, especially when combined with hyperspectral data, thanks to their abilities to extract more features and infer information (Guo et al., 2022). This allows more accurate and effective monitoring of plant health, going beyond the constraints of spectral indices in the past (Poornima & Edward, 2025). These approaches offer a more detailed insight into crop physiological responses to environmental stressors, which can be used to develop proactive management practices. In particular, 1D-CNNs are especially appropriate in processing hyperspectral data because their structure is inherently consistent with one-dimensional spectral data, and it can do well in the recognition of features and their retrieval of biochemical properties of leaves by convolution, pooling, and fully connected layers (Guo et al., 2022; Yang et al., 2023). This is also evidenced by the fact that 1D-CNNs are capable of learning particular spectral responses of droughtresistant genotypes, despite the dimensionality reduction methods used on full spectral data (Guo et al., 2022). Such deep learning models are able to see minute spectral variations that can be understood as drought stress in crops such as cotton and predict physiological parameters such as Fv/Fm accurately (Guo et al., 2022; Poornima and Edward, 2025).

CONCLUSION

This article shows conclusively that through the combination of hyperspectral remote sensing, thermal sensing, and advanced artificial intelligence, one can detect a wide variety of crop stresses, such as nitrogen deficiency, phosphorus deficiency, drought stress, and fungal disease, with a high degree of accuracy, early, and spatially explicit results. Out of nine tested models, Transfer Learning CNN has proven to be the most successful with a macro-average classification accuracy of 97.08, where the precision, recall, and F1-scores were above 95 percent across all stress classes. The model was able to detect drought stress up to 9.2 days before observable symptoms, and this is a critical time frame during which specific agronomic treatments can be made. The spectral analysis showed that the red-edge wavelength (710 nm) and Chlorophyll Index red-edge (CIred-edge) were the most discriminative ones, and an F-statistic of 145.67 among the stress conditions was obtained. All stress types had an accuracy of spatial mapping of more than 89% by Intersection over Union (IoU), which validates the usability of the model in precision agriculture applications. Moreover, the model generalized well in a variety of crops with maize having the highest average accuracy (97.53) and tomato having the lowest yet still good accuracy (96.81). The Transfer Learning CNN was also very slow to train (567.89 seconds), but it has a fast inference (0.67 ms per sample) rate, which is appropriate to implement in real time on unmanned aerial vehicles (UAVs). These results support the conclusion that hyperspectral imaging with deep transfer learning can be a transformative framework to use in proactive crop health management, eliminating the use of broad-spectrum treatments, reducing losses in yield, and facilitating sustainable intensification of agro-ecosystems in varying environmental conditions.

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