AI/ML APPLICATIONS IN AGRICULTURE: RETRIEVING WHEAT CROP TRAITS FROM UAV-BORNE HYPERSPECTRAL IMAGES USING HYBRID MACHINE LEARNING MODELS

Kunal Mahto[1], Subhash Chandra Dutta[2]

[1]PhD Scholar, Department of Computer Science & Engineering, BIT Sindri, Dhanbad, India, kunalm.rs.cse21@bitsindri.ac.in

[2]HOD, Department of Computer Science & Engineering, BIT Sindri, Dhanbad, India, scdutta@bitsindri.ac.in

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Abstract

In recent years, advances in agricultural operations have been made possible by the deployment of machine learning (ML) and artificial intelligence (AI) approaches. This shift has led to an increase in the visibility of crop management and yield optimisation in recent years. This study looks into the application of hybrid machine learning models to extract wheat crop characteristics from hyperspectral photos captured by unmanned aerial vehicles (UAVs). For this experiment, the ARTMO software package is employed. The workflow presented includes field testing, using unmanned aerial vehicles (UAVs) to take pictures, and using advanced data processing techniques like principal component analysis (PCA), Gaussian process regression (GPR), and PROSAIL simulations. NRMSE values for LAI and CCC are relatively low at 9.7% and 15.9%, respectively. These figures show that overall performance is excellent. These numbers suggest that the uncertainties have significantly decreased and that the retrieval accuracy was fairly good. There is an additional improvement in the model's precision as a result of the addition of non-vegetation spectra to the dataset optimised for AL. This approach provides a scalable, quantitative, and real-time solution for vegetative product surveillance. This approach is what has allowed for this important contribution to the field of precision agriculture.

Keywords: *Ai/Ml Applications, Hybrid Machine Learning Models, Wheat Crop, Uav-Borne Hyperspectral Images.*

1. INTRODUCTION

Lately, the coordination of artificial intelligence (AI) and machine learning (ML) procedures has reformed horticultural practices, especially with regards to crop the executives and yield improvement. One promising application involves the use of unmanned aerial vehicles (UAVs) equipped with hyperspectral imaging technology to capture detailed data on wheat crop traits.

These photos give extensive, high-resolution spectrum information that standard approaches cannot match, allowing the extraction of exact agricultural metrics like chlorophyll, leaf area index, and nutrient levels.

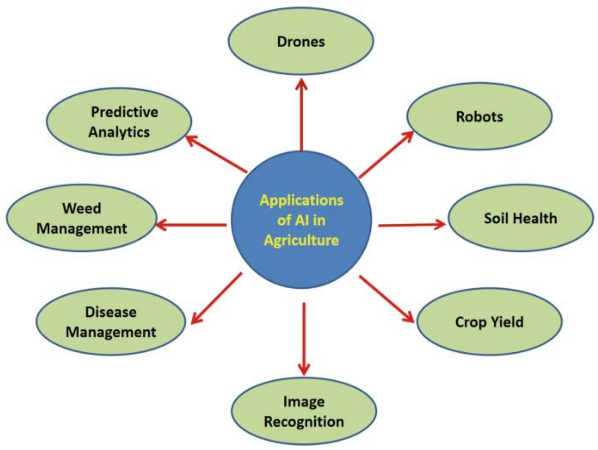

Figure 1: Applications of AI in Agriculture

Researchers may analyse and interpret these complex datasets using hybrid machine learning models that combine deep learning algorithms with statistical methods to give farmers insights into crop productivity and sustainability.

1.1.Wheat Crop Traits and Their Significance

Wheat, a staple crop worldwide, exhibits diverse traits such as leaf chlorophyll content, biomass accumulation, and nitrogen status, which are crucial indicators of crop health and productivity. Monitoring these traits throughout the growing season is essential for optimizing agricultural practices, including irrigation scheduling, fertilizer application, and disease management. Traditional methods of trait assessment, such as manual sampling and laboratory analysis, are labor-intensive, time-consuming, and often provide limited spatial coverage.

1.2.Objectives

The core objectives of the study are as follows:

1. To retrieve wheat crop traits (LAI and CCC) from UAV-borne hyperspectral images using hybrid machine learning models.

2. To implement a workflow with UAV imaging, PROSAIL simulations, GPR, and PCA for precise wheat crop monitoring.
3. To enhance trait retrieval accuracy by integrating non-vegetation spectra into the AL-optimized dataset.

2. LITERATURE REVIEW

Behera et al. (2010) Using the LAI-2000 Plant Canopy Analyzer, the study estimates Jatropha curcas leaf area index (LAI) indirectly. The canopy light transmittance method is essential for agricultural canopy structure and function assessment. The researchers used it to estimate LAI non-destructively, showing how technology-driven approaches can improve agriculture and forestry research precision and efficiency.

Francone et al. (2014) The Ceptometer and Pocket LAI Smart App estimated LAI differently for canopies with varying structures. The data suggest canopy design influences LAI measurements, emphasizing the necessity for canopy-specific methods. Agronomic and ecological LAI estimations may be more accurate and useful. The research optimizes LAI measurement for different canopy topologies and improves agricultural management.

Gonsamo and Pellikka (2008) Researchers corrected canopy LAI slope effects with hemispherical photography. The study indicated significant slope effects in LAI estimates, requiring adjustment. Statistics indicate that LAI estimate should employ topography to better ecological evaluations and management. The research improves hemispherical photography for varied environments, enabling ecological studies and conservation.

Liang et al. (2020) Researchers estimated agricultural Leaf Area Index using spectral feature extraction and hybrid inversion. Due to its accuracy, remote sensing can improve agricultural monitoring and management. This work improves LAI calculation methods to optimise agricultural production evaluations and resource management. Remote sensing aids sustainable agriculture and environmental protection.

3. APPLICATIONS OF AI/ ML IN AGRICULTURE

A portion of the AI/ML based applications in agriculture area are -

3.1. Yield prediction

Machine learning methods estimate crop yield using remote sensing. The majority use Artificial Neural Networks (ANN), then Convolutional Ones. Regularizing Bayes BP, SVR, ELR, RFR, and PLSR operate well. Red edge, canopy chlorophyll, and absorption ratio indices predict crop output. For efficient crop management, ML models with limited training data must estimate multi-stage crop production promptly.

3.2.Pest and diseases detection

Preventing output losses requires early crop disease identification. Accurate estimates require machine and deep learning. MLR models distinguished Maize Dwarf Mosaic Virus, wheat Powdery Mildew Disease, and Kiwifruit Decline Syndrome utilizing UAV information. These findings enable smart farming by recognising diseased crops, reducing pesticide and chemical consumption, and preserving crop quality. Figure demonstrates major deep and machine learning models.

3.3.Weed detection

Pests like weeds reduce crop yield and productivity. Early weed identification in farms is better with ML/DL. Drone, robot, and digital camera RGB images are processed using these algorithms. VGGNet performed worst, whereas SVM and CNN achieved 99% accuracy. This method processes RGB photos from drones, robotics, and digital cameras.

3.4.Soil health management

Food sustainability requires digital soil planning and shrewd supplement expectation. ML strategies like arbitrary woodland and profound learning beat traditional models for soil supplement expectation. Top soil nutrient prediction machine learning methods are compared.

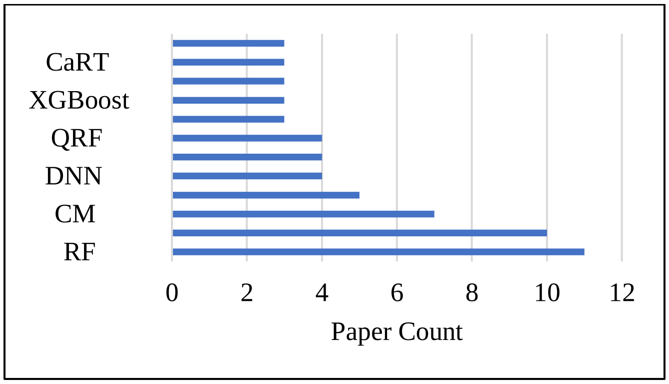

Figure 2: An illustration of the top 12 machine learning models for soil prediction

3.5.Crop quality management

Detecting advances and machine learning algorithms to monitor crop nitrogen and chlorophyll condition is crucial. Radiative exchange methods and machine learning have been combined to consolidate SWIR ghastly hyperspectral information. Using hybrid models, especially radiative exchange models with Gaussian cycle relapse, these limits have been recovered quickly and precisely.

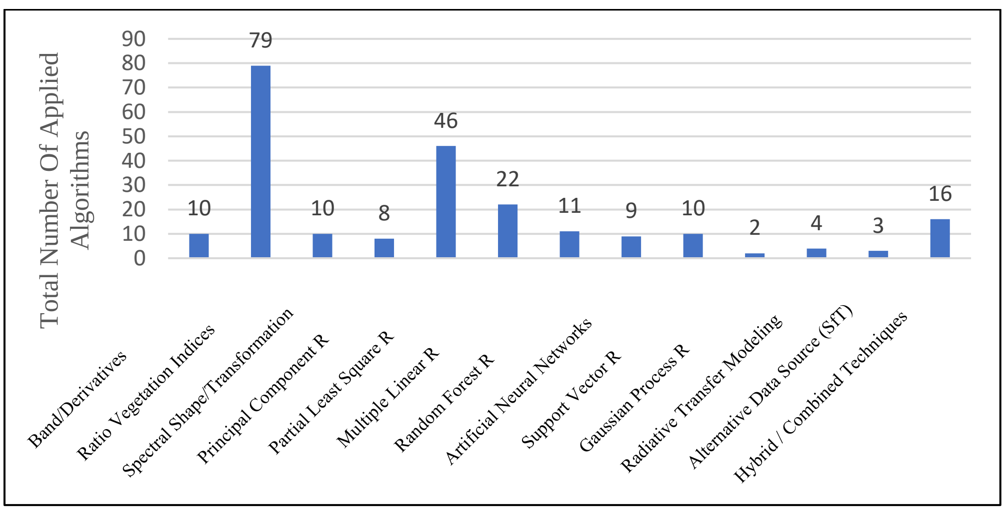

Figure 3: N content estimation using several techniques

3.6.Smart irrigation

The proposed machine learning-based water system design incorporates information from different sources, including UAV and satellite-caught information, soil, and climate data, into a cloud server. This empowers shrewd water system planning, forecasts, and proposals. The architecture recommends the use of supervised, unsupervised, reinforcement, and federated learning models for precise and smart field management.

3.7.Livestock Management

Livestock the board includes disease location, immunization, creation the executives, tracking, and wellbeing checking. These models show the most elevated exactness of more than close to 100% in steers recognizable proof, while profound learning models like ResNet, Origin, DenseNet, and NasNet additionally accomplish more than close to 100% precision.

4. METHODOLOGY

The block chart of the procedure utilized for the proposed approach is shown. The main advances engaged with the workflow are (I) field trial and error, UAV picture procurement, and pre-processing; (ii) PROSAIL reenactments and model assessment; (iii) Gaussian process regression (GPR); (iv) dimensionality decrease utilizing principal component analysis (PCA); and (v) dynamic learning techniques and field check. Each step is explained exhaustively in the resulting segments.

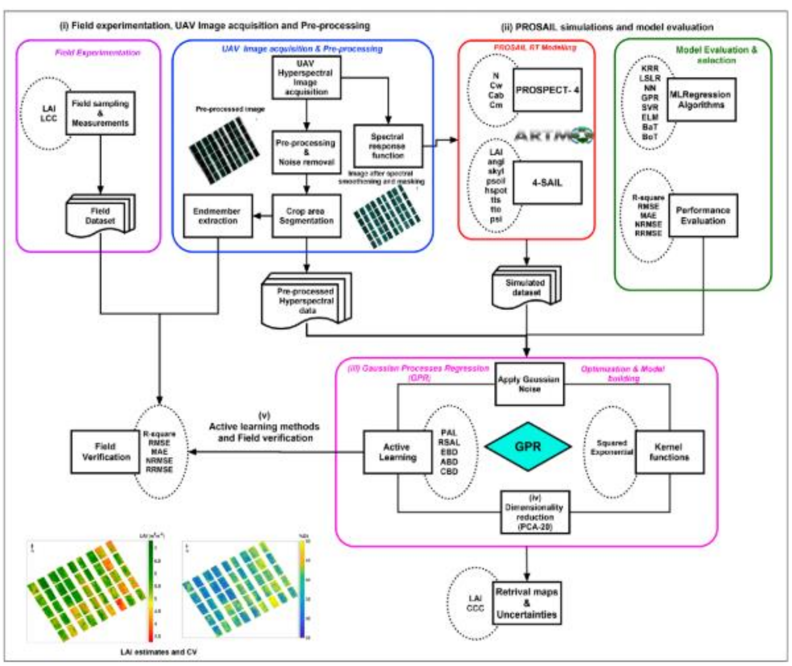

Figure 4: Block schematic of the study's methodology

The Study concentrated on an exploratory wheat crop at ICAR-IARI 228 meters above ocean level. The field has three replications of fifteen plots with five nitrogen grades and three water system systems. DMSO was utilized to anticipate agrarian yield and LAI-2000 plant covering analyzer to gauge LAI. The 21-m-high hyperspectral image has 278 400-1000 nm bands. UgCS Mission planning software designed the mission route, and Headwall Spectral View and ENVI analysed the gained hypercube.

4.1.Model Evaluation and Selection of GPR

A study assessed eight multivariate models for assessing LAI and CCC involving PCA as a dimensionality decrease technique. GPR beat any remaining models in foreseeing LAI with the most noteworthy R2 worth of 0.887, while KRR was appropriate for anticipating CCC with a R2 worth of 0.8889. MAE values for LAI and CCC were 0.128 and 0.127, separately, while RMSE values were 0.254 and 0.135. The least qualities for assessing LAI and CCC were 1.857% and 0.544%, separately. Both GPR and KRR created more exact and strong outcomes in assessing crop traits.

Table 1: Evaluation of MLRA models' accuracy in obtaining LAI and CCC

S. No.	Model	MLRA	MAE	RMSE	RRMSE (%)	NRMSE (%)
LAI						
1	GPR	0.128	0.254	3.887	1.857	0.887
2	KRR	0.225	0.264	5.176	2.195	0.006
3	NN	0.230	0.343	7.261	3.264	0.099
4	LS	0.290	0.358	7.656	3.466	0.098
5	ELM	0.290	0.432	9.510	4.468	0.089
6	BaT	0.329	0.468	10.570	4.965	0.087
7	BoT	0.414	0.524	11.944	5.715	0.074
8	SVR	0.445	0.559	12.903	6.207	0.068
CCC						
1	KRR	0.127	0.135	2.673	0.544	0.8889
2	GPR	0.142	0.154	3.867	0.857	1.000
3	NN	0.142	0.160	4.373	1.015	1.000
4	LS	0.149	0.160	4.403	1.023	1.000
5	ELM	0.153	0.174	5.226	2.25	0.999
6	SVR	0.186	0.104	7.110	2.710	0.996

7	BaT	0.179	0.210	8.216	2.080	0.996
8	BoT	0.240	0.287	12.632	4.203	0.991

The study shows smooth convergence and the usage of Non-Related Mean Square Error (NRRMSE) over R2 for LAI and CCC retrieval using Artificial Neural Network (ANN) methods. Validating with the field dataset shows that adding fresh samples to each AL iteration decreases RMSE and increases R2. With a few samples, the GPR model performed best, achieving 97 and 119 for LAI and CCC. For LAI, RSAL outperformed other AL methods, whereas EBD excelled for CCC. Low sampling size may cause convergence due to a small number of training data points.

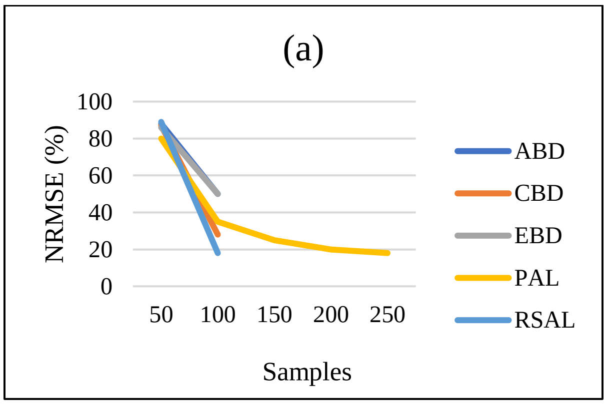

Figure 5 (a): NRMSE (%) is shown graphically for a number of trait estimates made using various AL techniques. (A) The number of samples is indicated by LAI# samples

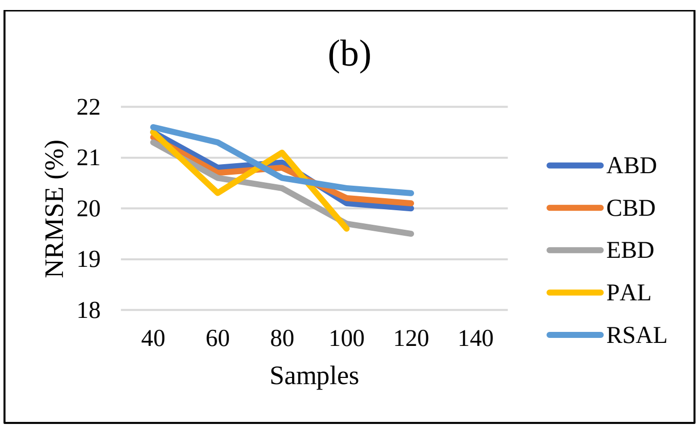

Figure 5 (b): NRMSE (%) is shown graphically for a number of trait estimates made using various AL techniques. (b) CCC. # samples indicates how many samples there are

4.2.Retrieval of LAI and CCC

Preprocessed UAV hyperspectral images was used to calculate and estimate uncertainty using final GPR models. CV, LAI, and CCC retrieval maps were shown. Experimental plots with low LAI and CCC values exhibited red pixels, showing pixel-wise volatility. The plots revealed realistic and appropriate spatial variability with maximum and minimum values. The estimated maps showed no zero or almost zero values, indicating that there were no non-vegetated areas, despite the fact that the GPR models were trained with non-vegetation spectra and trait values set to zero.

5. RESULTS

5.1. Performance and evaluation criteria (including KPIs)

The GPR models' 9.7% and 15.9% NRMSE values after field check demonstrate great recovery precision and more modest planning uncertainties for LAI and CCC. ARTMO, a free programming device, is utilized to recover wheat crop biophysical qualities from UAV datasets using a refined kernel-based and adaptable hybrid procedure.

Table 2 (a): Model Performance Metrics for LAI Prediction

Parameter	LAI
NRMSE	8.58%
RMSE	0.735%
MAE	0.481%
R^2	0.998%
Improved NRMSE	9.7% (from 17.9%)

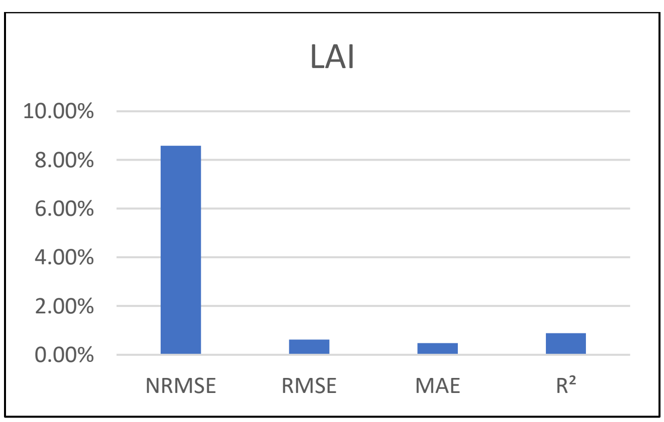

Figure 6 (a): Graphical presentation of the Model Performance Metrics for LAI Prediction

Table 2 (b): Model Performance Metrics for CCC Prediction

Parameter	CCC
NRMSE	15.95%
RMSE	0.668%
MAE	0.423%
R^2	0.767%
Improved NRMSE	15.9 % (from 19.4%)

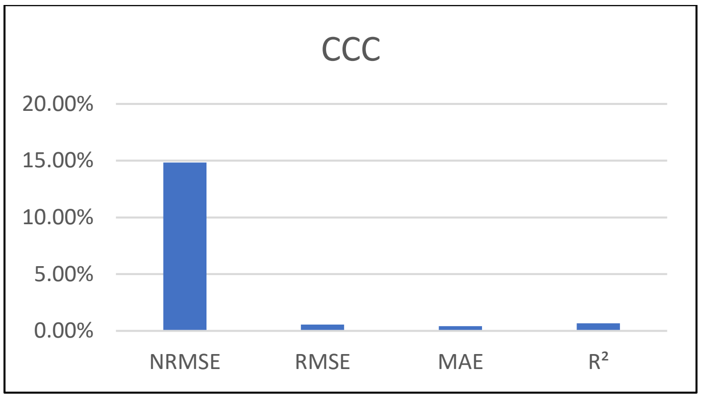

Figure 6 (b): Graphical presentation of the Model Performance Metrics for CCC Prediction

GPR models for LAI and CCC recovery have RMSEs of 0.735 and 0.668. LAI and CCC have MAE upsides of 0.481 and 0.423, individually, and R2 upsides of 0.998 and 0.767. NRMSE upsides of 8.589% and 15.953% for LAI and CCC recovery are the most basic measurable elements. NRMSE further developed essentially subsequent to adding nonvegetation spectra to the AL-upgraded dataset and retraining. From 17.9 to 9.7%, LAI NRMSE improved, and 19.4 to 15.9%, CCC diminished. Five uncovered soil or non-vegetation spectra (10% of in situ estimations) were added to the AL-advanced dataset before crop trait approval.

6. CONCLUSION

AI and ML can upset crop the board and yield enhancement in agriculture. This study shows how hybrid machine learning models can recover wheat crop ascribes from UAV-borne hyperspectral pictures utilizing ARTMO programming. Field tests, UAV picture gathering, and high-level information processing strategies including PROSAIL reenactments, Gaussian process regression

(GPR), and PCA are utilized. Brilliant recovery exactness and diminished uncertainties were shown by low normalized root mean square error (NRMSE) upsides of 9.7% for leaf area index (LAI) and 15.9% for canopy chlorophyll content (CCC). The dynamic learning-upgraded dataset including non-vegetation range works on model accuracy, making vegetation item observing adaptable, quantitative, and constant. This strategy further develops accuracy agriculture by checking crop wellbeing precisely and productively.

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