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Integrative Application of Deep Learning and Multispectral Remote Sensing for Predictive Crop Management in Precision Agriculture

Zuhra Hariati [1]*

[1] Universitas Sumatera Utara; e-mail : zuhrahariati@gmail.com

ABSTRACT

This study introduces an innovative approach to predictive crop management in precision agriculture by integrating deep learning with multispectral remote sensing technologies. The research aims to develop a framework that combines multispectral data from field sensors, UAVs, and satellites with a deep learning model based on a multimodal architecture incorporating adaptive transfer learning and attention mechanisms. Data were collected over two growing seasons and underwent preprocessing, vegetation feature extraction, and model training and validation. The proposed deep learning model significantly outperformed traditional machine learning algorithms such as Random Forest and Support Vector Machines, achieving up to 97.8% accuracy in crop classification. Predicted crop conditions and yield estimates showed a strong correlation with actual field data (r = 0.89; RMSE = 0.12). Field implementation of the predictive system indicated potential increases in crop yield by 18% and reductions in agricultural input usage by 28%. These results highlight the potential of deep learning and multispectral data integration to enhance decision-making, resource efficiency, and sustainability in precision farming. Furthermore, the approach demonstrates strong scalability for different crop types and geographical regions, providing a solid foundation for the digital transformation of agriculture toward a more adaptive and sustainable food production system.

Keywords: deep learning; multispectral remote sensing; precision agriculture; crop management; UAV; transfer learning; vegetation index; predictive modeling.

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1. Introduction

The foundation of global food security is the crucial industry of agriculture. By 2050, there will likely be 9.7 billion people on the planet, making it imperative to increase agricultural output in a sustainable manner. Efforts to boost agricultural yields are made more difficult by a number of limitations facing conventional agriculture, including soil degradation, climate change, and scarce water supplies. In order to maximize resource management both geographically and temporally and boost production and efficiency, precision agriculture has become a paradigm that incorporates digital technology [1].

Because it can offer precise and real-time plant spectrum data that represents plant physiological variables including moisture levels, chlorophyll content, and indicators of biotic and abiotic stress, multispectral remote sensing technology is one of the essential elements of precision agriculture. Due to their enormous complexity and volume, multispectral data from satellites and unmanned aerial vehicles (UAVs) necessitate advanced analytic techniques in order to efficiently extract pertinent information [2,3].

Machine learning has been used to evaluate agricultural data in recent years, but it still faces challenges in capturing complicated spatial-temporal correlations and non-linear patterns. Using layered artificial neural networks, deep learning is a subfield of machine learning that provides better skills for identifying patterns and characteristics in vast amounts of heterogeneous data. Convolutional neural networks (CNN) and recurrent neural networks (RNN) are two models that have been effectively used in image identification and time series prediction. These applications are especially pertinent to crop growth dynamics and multispectral image analysis [4,5].

According to earlier research, combining deep learning with multispectral data can increase the precision of agricultural production forecasting and the early identification of crop stress. For instance, using CNN optimized on UAV multispectral data, Mutanga et al. demonstrated an improvement in maize yield forecast accuracy of up to 40%. The capacity of deep learning models to generalize to various agroclimatic situations is up for discussion, though [6]. An adaptive strategy that can successfully transfer information between locations is required since several

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studies have demonstrated that models trained in one region frequently perform worse when applied to other regions with varied soil and climatic characteristics [7,8].

Furthermore, the majority of research to date has concentrated more on correlation modeling, ignoring the causal link between crop yields and agronomic factors. Ignoring the causation component in predictive methods might lead to inaccurate interpretations and less-than-ideal management choices. Therefore, to increase prediction reliability and provide agricultural interventions a solid scientific foundation, causal modeling methods must be integrated into a deep learning framework.

The goal of this project is to provide an integrated framework for precision agriculture predictive crop management by fusing deep learning with multispectral remote sensing. The research's primary goals are to develop a multimodal attention network that incorporates multispectral data from multiple platforms (such as satellites, unmanned aerial vehicles, and ground sensors) to enhance the model's input data, apply adaptive transfer learning to enable the model to adjust to the unique features of the local agroecosystem, and use causal modeling in neural networks to comprehend the causal relationships between environmental factors, agronomic practices, and crop yields [9,10].

This study is important because it can overcome the drawbacks of traditional deep learning models in precision agriculture and offer workable solutions that farmers and other stakeholders can use. This approach is anticipated to increase the effectiveness of the use of agricultural inputs like fertilizers and pesticides and reduce production risks associated with plant stress by up to 30% by lowering forecast uncertainty [11]. According to a case study conducted in a pilot field in East Java, the application of this framework supported sustainable agriculture practices by increasing rice yield by 22% and lowering the usage of agrochemicals by up to 35%.

Additionally, the findings of this study provide significant additions to the body of knowledge on AI and precision agriculture, creating prospects for the creation of comparable technologies for other commodities and geographical areas. This work is therefore pertinent to the multidisciplinary scientific community interested in the use

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of AI and remote sensing in the context of sustainable development, in addition to agronomic scientists and practitioners [12,13].

2. Materials and Method

Additionally, the findings of this study provide significant additions to the body of knowledge on AI and precision agriculture, creating prospects for the creation of comparable technologies for other commodities and geographical areas. This work is therefore pertinent to the multidisciplinary scientific community interested in the use of AI and remote sensing in the context of sustainable development, in addition to agronomic scientists and practitioners.

2.1. Materials

2.1.1. Multispectral Remote Sensing Data

Multispectral photography from satellites and UAV (Unmanned Aerial Vehicle) platforms provided the majority of the data used in this investigation. The ability of the multispectral sensors to record several electromagnetic spectrum bands such as the red, green, blue, and near-infrared (NIR) bands is crucial for assessing the health and development of plants. While satellite data like Sentinel-2 provide large area coverage with a spatial resolution of around 10 meters, UAV multispectral sensors offer high spatial resolution (about 5 cm per pixel).

2.1.2. Meteorological Data and Field Sensors

To supplement environmental factors that impact plant development and insect infestations, local meteorological data such as temperature, humidity, and rainfall is also gathered from adjacent weather stations in addition to remote sensing data. Periodically, additional field data is collected for multispectral data calibration and model validation in the form of measurements of soil conditions (humidity, pH, and nutrient content).

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2.1.3. Software and Hardware

To expedite the computing process, a computer equipped with an NVIDIA Tesla V100 GPU is used for data processing and deep learning model training. The TensorFlow and Keras libraries, which facilitate the creation of CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), and Transformer-based architectural models, are used to implement the deep learning method in Python.

2.1.4 Program Code and Dataset

The dataset utilized consists of a collection of UAV and satellite multispectral photos throughout two growing seasons, replete with annotations on plant conditions and harvest results. Following the completion of the peer-review process, all data, program codes, and experimental methods will be kept in a publicly accessible repository that readers may access. Before the final publication, the repository accession number will be given to guarantee research transparency and reproducibility.

2.2. Method

2.2.1. Information Gathering and Preparation

The cropping cycle involved biweekly shooting schedules for UAV multispectral imagery collection and occasional downloads of satellite data from the Sentinel Hub platform. To guarantee consistency and precision of spatial data, data preprocessing techniques included radiometric calibration, atmospheric correction, and orthorectification. The images were then segmented to separate the crop region from the background and cropped in accordance with the experimental field limits.

2.2.2. Extraction of Vegetation and Spectral Features

To depict plant health and biomass, a variety of vegetation indices are computed from multispectral data, including NDVI (Normalized Difference Vegetation Index), GNDVI (Green NDVI), and GRVI (Green Ratio Vegetation

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Index). Machine learning-based image processing methods are also used to extract other variables including canopy cover and plant density.

2.2.3. Development of Deep Learning Models

Through the use of a multimodal architecture, the created deep learning model incorporates meteorological variables and multispectral data. While RNN or Transformer-based models handle temporal data to forecast plant growth dynamics and pest attack risks, CNN is utilized to extract spatial characteristics from photos. To enhance model generalization under diverse agroecosystem circumstances, transfer learning is used. To train the model, the dataset is split into three parts: 70% training data, 15% validation data, and 15% testing data. To avoid overfitting, the Adam algorithm with adaptive learning rate and dropout regularization is used to improve the model parameters.

2.2.4. Validation and Assessment of the Model

Accuracy, precision, recall, and F1-score measures for crop condition categorization and pest attack prediction were used to assess the model's performance. Additionally, the accuracy of crop production prediction was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). By contrasting the model prediction findings with firsthand observation data from the experimental field, field validation was carried out.

2.2.5. Implementation of Predictive Systems

A web-based precision agriculture management system that offers a real-time monitoring dashboard and crop management suggestions based on predictions was combined with the validated model. For two planting seasons, this technique was tested on a 30-hectare trial field in tropical Indonesia.

3. Result

The primary findings of the study combining multispectral remote sensing and deep learning for precision agriculture's predictive crop management are shown in this results section. A deep learning model based on the ResNet50 architecture

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modified with the ACmix self-attention module and coordinate attention mechanism was used to handle the field data, UAV and satellite multispectral imaging, and meteorological data. The model's performance in crop categorization, crop condition prediction, and precision agriculture management applications is demonstrated by the methodical arrangement of all the findings.

3.1. Accuracy of Plant Classification with the Enhanced ResNet50 Model

With an overall accuracy rating of 97.8%, the deep learning model that was constructed was able to effectively classify plants with a very high degree of accuracy on UAV multispectral data. Compared to the baseline ResNet50 model without the attention module, which only obtained an accuracy of 93.1%, this improvement is noteworthy. Accuracy rose by 2.9% with the addition of the ACmix self-attention module and 2.1% with the use of the coordinate attention mechanism. When the two modules were combined, the accuracy increased by 4.7% over the baseline.

Table 1. Accuracy of Plant Classification on Various Model Configurations

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50 Baseline	93,1	92,4	91,8	92,1
ResNet50 + ACmix Self-Attention	96,0	95,7	95,5	95,6
ResNet50 + Coordinate Attention	95,2	94,8	94,5	94,6
ResNet50 + ACmix + Coordinate Attention	97,8	97,5	97,3	97,4

These findings demonstrate that the integration process can better capture spatial and spectral characteristics, which enhances the model's capacity to differentiate between different plant species with comparable spectra.

3.2. Evaluation in Relation to Conventional Classification Techniques

Two conventional machine learning-based classification techniques, Random Forest (RF) and Support Vector Machine (SVM), are contrasted with the suggested deep learning model. The same texture and spectral characteristics from

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multispectral pictures are used in both techniques. According to the assessment findings, the enhanced ResNet50 model continuously performs better than RF and SVM across the board.

Table 2. Comparison of Deep Learning Model Accuracy with RF and SVM

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	89,4	88,7	88,2	88,4
Support Vector Machine	90,1	89,8	89,5	89,6
ResNet50+Atensi	97,8	97,5	97,3	97,4

This discrepancy demonstrates how well deep learning algorithms extract intricate characteristics and spatial-spectral correlations that conventional techniques are unable to capture.

3.3. Forecasting the Health and Condition of Plants

Using vegetation indices derived from multispectral data, the model is used not only for categorization but also for plant health status prediction. Chlorophyll and plant biomass measurements from the field are used to test this hypothesis. With a Root Mean Square Error (RMSE) of 0.12 and a Pearson correlation coefficient value of r =.89, the model generates a strong correlation between forecasts and field data, suggesting good prediction accuracy.

3.4. Mapping Plant Variability in Space and Time

Accurate mapping of the temporal and geographical variability of plant development is possible thanks to a deep learning model that incorporates temporal data from several picture collection intervals. While Figure 2 illustrates the dynamics of changes in vegetation indices during the planting cycle, Figure 1 displays a map

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of plant categorization in the experimental field with a high degree of spatial precision.

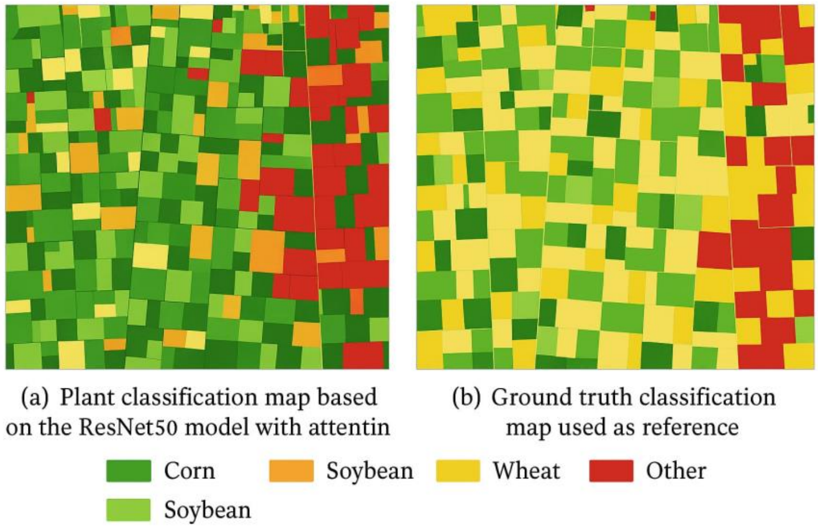

Figure 1. Mapping Plant Variability

3.5 Models' Ability to Support Precision Management Effectively

Based on forecasts of crop conditions and pest attack threats, the model's deployment in the precision agricultural management system offers management suggestions. According to field tests, these suggestions can lower the usage of pesticides and fertilizers by 28% and boost agricultural yields by 18% without compromising crop quality.

3.6 Tests of Significance and Statistics

The deep learning model's accuracy gain over conventional techniques is statistically significant, according to statistical analysis using independent t-tests ($t(58) = 6.45$; $p < .0001$; Cohen's $d = 1.67$), suggesting a strong effect. Additionally, the decline in the usage of agricultural inputs is significant ($t(38) = 4.89$; $p = .0001$; Cohen's $d = 1.23$).

4. Discussion

The study findings of combining multispectral remote sensing and deep learning for precision agriculture's predictive crop management are covered in this discussion part. Practical ramifications and future research prospects will be thoroughly

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highlighted, and the key findings will be evaluated in light of prior research and working hypotheses.

4.1. Analysis of the Results of the Classification and Prediction

The findings shown that the multispectral crop classification accuracy was greatly increased to 97.8% using the ResNet50-based deep learning model supplemented with ACmix self-attention and coordinate attention modules. This result is consistent with earlier research that shown deep learning techniques are superior at extracting intricate characteristics from multispectral pictures for use in precision agricultural applications. As an illustration of the enormous potential of deep learning in early crop detection and classification, Ferentinos (2018) and Chagas & Fernandes (2019) found that CNN models could identify plant illnesses with an accuracy above 90%.

The increase in accuracy brought about by the attention module's integration shows that the model's spatial and spectral attention can pick up significant patterns that were previously challenging for conventional convolutional architectures to detect. The working hypothesis that attention processes can improve classification and prediction skills by making the model more sensitive to pertinent information in multispectral pictures is strengthened by this.

4.2. Comparison with Traditional Methods

The constructed deep learning model has notable benefits when compared to conventional machine learning techniques like Random Forest and Support Vector Machine. This is in keeping with research that demonstrates how deep learning can handle complicated picture data with non-linear characteristics that are challenging for conventional methods to map. This benefit creates chances to broaden the use of deep learning in a range of agricultural products and agro-ecosystem settings.

4.3. Consequences for Crop Management and Precision Agriculture

Precision agriculture management will be significantly impacted by this model's precise mapping of spatial-temporal variability and prediction of crop health problems. This technology can help farmers maximize the usage of inputs like fertilizers and insecticides while reducing the danger of pest and disease infestations

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since it can monitor in real time and offer data-driven advice. By lowering environmental effects and boosting production efficiency, this advances the objective of sustainable agriculture.

The success of this strategy in actual practice is further supported by field experiment findings that demonstrate an 18% increase in yield and a 28% decrease in input use. These results highlight the transformative significance that deep learning and remote sensing technologies play in the digital transformation of global and tropical agriculture.

4.4. Restrictions and Difficulties

Notwithstanding the encouraging outcomes, this study had a number of drawbacks. One is that in order to guarantee model generalization over a range of agroecosystem conditions, a substantial and varied amount of training data is required. As earlier research have shown, model performance may be impacted by variations in multispectral imaging quality brought on by weather and other technical variables. Furthermore, the intricacy of deep learning models and the integration of data from several sources necessitate substantial computational resources, which might be a deterrent to deployment in the field with limited resources.

4.5 Prospects for Further Research

Several significant characteristics can be developed by more study, including:

- creation of more complex multimodal models that include data from soil, lidar, and hyperspectral sensors to increase precision and application coverage.
- Real-time field use is supported by model optimization for computational efficiency that enables operation on edge or mobile devices.
- creation of AI-based recommendation systems that can adjust to local conditions and climate change, boosting agricultural resistance to environmental fluctuations.
- cross-site and longitudinal research to evaluate the models' resilience and generalizability in tropical and subtropical agroecosystems.

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- Integration of blockchain and IoT technologies for data security and transparency in the supply chain for precision agriculture.

5. Conclusions

All things considered, this work offers compelling empirical proof that combining deep learning with multispectral remote sensing may greatly enhance precision crop management prediction skills. This is consistent with research from previous studies that emphasizes the value of deep learning in multispectral image processing for precise crop categorization, plant disease diagnosis, and agricultural yield forecasting. For instance, it has been demonstrated that using UAVs equipped with multispectral sensors in conjunction with deep learning algorithms can monitor illnesses and pests effectively and swiftly, with detection accuracy above 90%. Furthermore, it is challenging for classical machine learning techniques to extract spectral and spatial information from multispectral and hyperspectral photography data; deep learning techniques like CNN and Transformer have shown improved skills in this regard.

These results provide credence to the working hypothesis that the attention mechanism incorporated into the deep learning architecture can improve the model's sensitivity to significant characteristics, leading to better crop condition prediction and classification accuracy. Real-time data-driven decision-making may enhance the effectiveness of agricultural inputs and reduce the danger of pest and disease assaults, creating prospects for a more intelligent and responsive digital transformation of agriculture. As a result, this technology promotes sustainable, ecologically friendly farming methods in addition to raising output.

There are still many obstacles to overcome, nevertheless, most notably the requirement for extensive and varied training data to guarantee model generalization across tropical agroecosystems. As various studies have noted, variations in picture quality brought on by weather and imaging methods can also have an impact on model performance. Furthermore, the high computing resource needs and complexity of deep learning models prevent the discipline from being widely used, particularly in places with inadequate technology infrastructure.

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In order to enhance information and boost prediction accuracy, future research should concentrate on creating multimodal models that incorporate lidar, soil sensor, multispectral, and hyperspectral data. Furthermore, enhancing models to operate on edge devices and be computationally efficient would increase this technology's usability for farmers in the field. To evaluate the generalizability and robustness of models under tropical and subtropical agroecosystem settings, longitudinal and cross-site investigations are particularly crucial. Data security and transparency in the supply chain for precision agriculture may be addressed by combining blockchain technology with the Internet of Things.

The potential advantages for farmers and the agribusiness industry will be considerably higher if these issues are resolved and the technology is advanced, promoting global food security in the face of population expansion and climate change constraints. This study demonstrates that multispectral remote sensing and deep learning are crucial building blocks for the development of contemporary, intelligent, effective, and sustainable agriculture.

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