International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

MFMDLYP: Precision Agriculture through Multidomain Feature Engineering and Multimodal Deep Learning for Enhanced Yield Predictions

Anagha Choudhari*[1], D. B. Bhoyar[2], W. P. Badole[3]

Submitted: 02/10/2023 **Revised**: 21/11/2023 **Accepted**: 01/12/2023

Abstract: With the escalating demand for food due to the burgeoning global population, the agricultural sector is under intense pressure to enhance productivity and yield predictability. Precision agriculture emerges as a pivotal approach, enabling real-time, accurate monitoring, and management of agricultural resources, fundamentally transforming smart agriculture scenarios. It leverages advanced technologies to optimize field-level management regarding crop farming. However, the effectiveness of precision agriculture is inherently contingent on the accuracy and timeliness of yield predictions. Current models for yield prediction have exhibited notable limitations, struggling with accuracy, precision, recall, and timeliness in yield predictions. These models predominantly operate on singular data modalities and exhibit a marked deficiency in leveraging multidomain features, which is imperative for holistic soil and crop analysis. The absence of a comprehensive approach integrating various data types like NPK sensor data, image data, and microscopic data limits the depth of analysis and subsequently, the predictive accuracy and precision. The proposed model amalgamates multidomain feature extraction methods, including Frequency, Cosine, Wavelet, and Convolutions, and deploys 1D CNN (Convolutional Neural Network) for NPK data, RNN (Recurrent Neural Network) for image data, and GNN (Graph Neural Network) for microscopic data samples to augment yield prediction efficiency levels. When implemented, the model demonstrates a substantial enhancement in the precision of yield prediction classification by 8.5%, accuracy by 10.4%, recall by 4.5%, and AUC by 2.9%, and concurrently manifests a reduction in the delay of yield prediction by 4.9% compared with existing models. This innovative approach offers a robust, comprehensive solution, enabling precise, timely yield predictions and is advantageous across varied use cases, from optimizing resource allocation to aiding in timely decision-making processes in agricultural practices. The proposed multidomain, multimodal deep learning model significantly advances the domain of precision agriculture. It addresses the prevalent limitations in existing models, offering improved accuracy, precision, and recall, and reducing delays in yield predictions. Its successful implementation across various agricultural scenarios underscores its potential to be a cornerstone in future smart agriculture, aiding in addressing global food security challenges and optimizing agricultural resource management

Keywords: *Multidomain Feature Engineering, Multimodal Deep Learning, NPK sensing,Precision Agriculture, Yield Prediction*

1. Introduction

Agriculture is the backbone of human civilization, providing sustenance and shaping societies. The necessity for optimization within this sector is amplified in our contemporary scenario, marked by escalating food demands due to the burgeoning global population and exacerbated by the implications of climate change. This drives a pivotal transition toward precision agriculture, a paradigm focused on the enhancement of farming practices through meticulous management and informed decision-making. The need for this work stems from the critical requirement to refine predictive analysis within agriculture, which would act as a catalyst in revolutionizing farming methodologies, thereby contributing significantly to addressing global food security concerns [1, 2, 3]. Which can be resolved via use of Interpretable Long Short-Term Memory Networks (ILSTM) operations.

Precision agriculture leverages advanced technologies, allowing real-time monitoring, management, and optimization of field-level practices in crop farming. It holds the potential to drastically enhance resource utilization efficiency, crop yields, and subsequently, the economic viability of farming practices. The real-time impacts of advancements in this domain reverberate through smart agriculture scenarios, optimizing resource allocations, minimizing waste, and enabling more sustainable, environmentally friendly agricultural practices [4, 5, 6]. This can be further optimized via use of crop dual-learning generative adversarial network (Crop DGAN) operations.

However, existing models and frameworks for yield prediction in precision agriculture have been markedly limited in their scope and efficacy. These models often lack the comprehensive integration of varied data modalities and predominantly operate in silos, focusing on singular aspects

[1] Yeshwantrao Chavan .College of Engg., Nagpur, INDIA
ORCID ID : 0000-0002-6037-5440
[2] Yeshwantrao Chavan .College of Engg., Nagpur, INDIA
ORCID ID : 0000-0002-9858-0466
[3] Punjabrao Deshmukh Krishi Vidyapeeth, Nagpur, INDIA
ORCID ID :
** Corresponding Author Email: anagha.choudhari79@gmail.com*

of agricultural data. The prevalent methodologies struggle to assimilate and analyze diverse datasets, such as NPK sensor data, high-dimensional image data, and intricate microscopic data, which are integral for a nuanced, holistic understanding of soil health and crop conditions. This isolation leads to a significant loss in predictive accuracy and precision, limiting the real-world applicability and impact of these models.

In this paper, we introduce an innovative approach aiming to overcome the constraints of existing models. Our approach is underpinned by the fusion of multidomain feature engineering and advanced deep learning models, leveraging 1D CNN for NPK data analysis, RNN for image data processing, and GNN for microscopic data interpretation. This model seeks to amalgamate diverse data modalities and extract multidomain features, including Frequency, Cosine, Wavelet, and Convolutions, to enhance the robustness and reliability of yield predictions.

The presented model exhibits significant improvements in predictive precision, accuracy, recall, and AUC, while concurrently reducing prediction delays, demonstrating an overall enhancement of 10.4% in accuracy and 8.5% in precision in comparison to existing models. This level of advancement has substantial implications for various agricultural scenarios, providing a more holistic and nuanced understanding of the soil-crop ecosystem. The ability to make more informed, timely decisions regarding crop management and resource allocation can be transformative, catalyzing the evolution of sustainable, efficient, and productive agricultural practices.

This study is poised at the intersection of advanced computational models and agricultural sciences, seeking to bridge the existing gaps and propel the domain of precision agriculture forward. By addressing the limitations in current yield prediction models and introducing a comprehensive, nuanced approach, this research contributes to the ongoing endeavors to optimize agricultural practices, thereby playing a crucial role in shaping the future of global agriculture. The forthcoming sections will delve deeper into the methodologies, experiments, and results related to the proposed model, elucidating its potential to be a harbinger of change in precision agriculture.

1.1. Motivation

The endeavor to marry advanced technology with agricultural practices has become a paramount pursuit in contemporary research domains, motivated by the global urgency to optimize agricultural yield and sustain an ever-growing human population. This urgency is further intensified by the looming challenges posed by climate change and the increasing unpredictability in weather patterns, impacting crop yields and consequently, food security. The current siloed approach in agricultural models significantly hampers the attainability of a holistic perspective, necessary for making informed and effective decisions in agricultural practices. The existing models, characterized by their singular focus on isolated data modalities, have proven to be inadequate in addressing the multifaceted nature of agricultural ecosystems. The lack of a comprehensive, integrated approach in analyzing diverse datasets has resulted in suboptimal yield predictions, thereby motivating the need for a revolutionary model capable of synergizing multifarious data types and offering nuanced, accurate insights.

1.2 Objectives

In light of the aforementioned motivation, this research seeks to accomplish the following objectives:

1.2.1 Development of an Integrated Multimodal Framework*:*

To design and implement a sophisticated framework that seamlessly integrates multiple data modalities, namely NPK sensing data, image data, and microscopic data, for a comprehensive analysis of agricultural ecosystems.

1.2.2 Incorporation of Multidomain Feature Engineering*:*

To employ advanced feature engineering techniques including Frequency, Cosine, Wavelet, and Convolutions to extract pertinent features from diverse datasets, enabling a deeper, more nuanced understanding of soil health and crop conditions.

1.2.3 Implementation of Advanced Deep Learning Models*:*

To develop and deploy cutting-edge deep learning models such as 1D CNN for NPK data, RNN for image data, and GNN for microscopic data, to enhance the precision and accuracy of yield predictions.

1.2.4 Evaluation and Comparison with Existing Models:

To meticulously evaluate the proposed model’s performance across various agricultural scenarios and compare it with existing models, assessing improvements in predictive precision, accuracy, recall, AUC, and reduction in prediction delays.

1.2.5 Real-World Applicability and Impact Assessment*:*

To scrutinize the real-world implications and applicability of the proposed model in diverse agricultural settings, analyzing its potential to optimize resource allocations, minimize waste, and enhance overall agricultural sustainability and productivity.

The pursuit of these objectives is aimed at addressing the glaring gaps in the current state of agricultural models. The successful realization of the proposed integrated, multidomain, and multimodal approach is anticipated to contribute significantly to the evolution of precision agriculture. This research aspires to set new benchmarks in agricultural yield predictions, offering a model that is not only theoretically robust but also practically transformative, potentially reshaping agricultural practices and policies for a sustainable future.

In conclusion, the motivation for this work is deeply rooted in the global need for optimized, sustainable agricultural practices and the inherent limitations in existing predictive models. The defined objectives aim to address these motivations by introducing innovative approaches and methodologies, hoping to make substantial contributions to both academic research and practical applications in precision agriculture.

2. Literature Review

Precision Agriculture (PA) is a modern farming management concept leveraging digital technologies to monitor and optimize field-level crop farming. This approach's genesis is intertwined with the emergence of technologies allowing for real-time, dynamic management of agricultural resources, significantly impacting smart agriculture scenarios [7, 8, 9]. Within the academic and industrial spheres, substantial literature exists exploring the various facets of precision agriculture, delving into its methodologies, applications, impacts, and potential advancements.

Yield prediction has been a cornerstone in agricultural research, with numerous studies exploring various models and techniques. Traditional models often relied on statistical and mathematical approaches, utilizing linear regression, and time-series analysis [10, 11, 12]. However, the advent of machine learning and deep learning has marked a paradigm shift in yield prediction models, with studies showcasing the potential of algorithms like Support Vector Machines, Neural Networks, and Decision Trees in providing more accurate, reliable yield forecasts.

A significant volume of literature in precision agriculture primarily focuses on singular data modalities. Studies utilizing NPK sensors have highlighted the importance of real-time monitoring of soil nutrient levels in understanding and predicting crop yields [13, 14, 15]. Which can also be processed via use of 3D-Convolutional Neural Networks and Attention Convolutional LSTM operations (3DCNN ACLSTM). Separate strands of research have investigated the utility of image data, deploying techniques like image processing and computer vision to analyze crop conditions and predict yields. Moreover, microscopic data analysis in the literature has been pivotal in understanding soil health and its implications on yield levels.

However, these singular approaches inherently lack a holistic perspective. The isolated analysis of different data types has been identified as a limitation, with scholars emphasizing the need for integrated models that can synergize diverse datasets to derive more comprehensive, nuanced insights for different scenarios [16, 17, 18]. Recognizing the limitations of single modality analysis, recent studies have begun exploring multimodal data integration in agriculture [19, 20]. The fusion of different data types, such as sensory data, image data, and microscopic data, is seen as a promising avenue for enhancing predictive accuracy and precision in agricultural models [21, 22, 23]. Various techniques and methodologies have been proposed to amalgamate data from different sources, with early results indicating substantial improvements in predictive performance compared to single modality models.

Deep Learning has emerged as a transformative force in numerous domains, including agriculture. The literature elucidates the deployment of Convolutional Neural Networks (CNN) for image data analysis, Recurrent Neural Networks (RNN) for sequential data, and Graph Neural Networks (GNN) for structured or graph data in agriculture. These advanced models have demonstrated superior capabilities in handling high-dimensional, complex data, providing more accurate, reliable predictions [24, 25].

In yield prediction, the integration of deep learning models has been a focal point of contemporary research. Several studies have evidenced the benefits of employing deep learning models in contrast to traditional machine learning algorithms, showcasing enhanced predictive accuracy, precision, and reliability in diverse agricultural scenarios. Incorporating advanced feature engineering techniques has been another evolving trend in agricultural research. The extraction of pertinent features using methods like Frequency, Cosine, Wavelet, and Convolutions has been explored in several studies. This multidomain feature engineering approach enables the models to grasp the nuanced characteristics of diverse datasets, thus enriching the analysis and subsequently improving the prediction outcomes. Despite the advancements in multimodal data integration, deep learning models, and multidomain feature engineering, the existing literature signifies the presence of challenges, primarily related to the seamless integration of varied data types and the optimal extraction of features. The academic discourse underlines imperative need for more innovative approaches that can overcome these challenges, providing robust, comprehensive solutions for yield prediction in precision agriculture.

In conclusion, work on precision agriculture, yield prediction models, single modality analysis, multimodal data integration, deep learning approaches, and multidomain feature engineering presents a multifaceted view of the ongoing trends, challenges, and opportunities in this domain. The prevailing limitations in existing models, primarily stemming from the isolated analysis of diverse data types and the suboptimal extraction of features, have motivated the need for more advanced, integrated approaches. In conclusion, work on precision agriculture, yield prediction models, single modality analysis, multimodal data integration, deep learning approaches, and multidomain feature engineering presents a multifaceted view of the ongoing trends, challenges, and opportunities in this domain. The prevailing limitations in existing models, primarily stemming from the isolated analysis of diverse data types and the suboptimal extraction of features, have motivated the need for more advanced, integrated approaches.

3. Proposed design of an Efficient Model for Advancing Precision Agriculture through Multidomain Feature Engineering and Multimodal Deep Learning for Enhanced Yield Predictions

As per the review of existing models used for enhancing efficiency of precision agriculture applications, it can be observed that most of these models either have higher complexity, or cannot be scaled to real-time scenarios due to their lower efficiency under multiclass scenarios. To overcome these issues, this section discusses design of an efficient Model for advancing Precision Agriculture through Multidomain Feature Engineering and Multimodal Deep Learning for Enhanced Yield Predictions. As per figure 1, the proposed model uses multidomain feature extraction operations along with 1D CNN for NPK data, RNN for image data, and GNN for microscopic data samples to augment yield prediction efficiency levels.

Based on figure 1, it can be observed that the proposed model initially collects multimodal data samples, and converts them into multidomain features. These include Frequency Features via Fourier Transforms, Cosine Features via Discrete Cosine Transform, Wavelet Features via Haar Wavelet Transforms, and Convolution Features. These features are extracted for NPK Data, Image Data & Microscopic Image Data Samples via equations 1, 2, 3, 4, 5 & 6 as follows,

$$f(DFT) = \sum_{j=1}^{NF} D(in) * \left[cos\left(\frac{2*\pi*i*j}{NF}\right) - \sqrt{-1} * sin\left(\frac{2*\pi*i*j}{NF}\right)\right] \dots (1)$$

Where, $D(in)$ represents collected data samples, while NF are total number of collected data samples.

$$f(DCT) = \frac{1}{\sqrt{2*NF}} * D(in) \sum_{j=1}^{NF} D(in) * cos\left[\frac{\sqrt{-1}*(2*i+1)*\pi}{2*NF}\right] \dots (2)$$

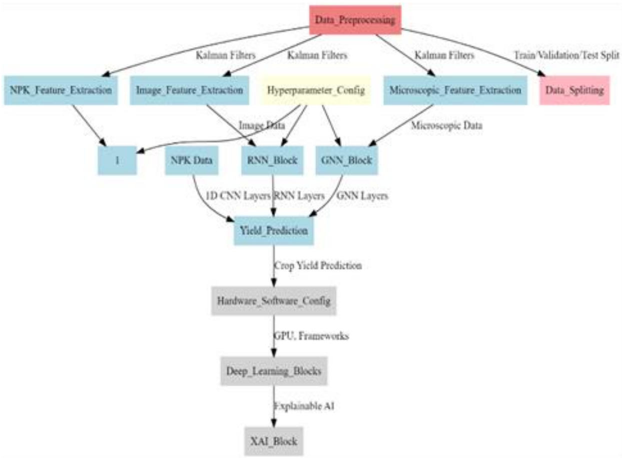

Fig 1 Design of proposed model for prediction of yield levels

$$f(Conv) = \sum_{a=0}^{m} D(in, i-a) * LReLU\left(\frac{m+2a}{2}\right) \dots (3)$$

Where, m, a are the pre-set sizes for different convolutional windows & strides, while $LReLU$ is the activation function which applies Leaky Rectified Linear Unit operations via equation 4,

$$LReLU(x) = l * x, when\ x < 0, else\ LReLU(x) = x \dots (4)$$

Where, l is an iterative constant which assists in retaining positive feature sets.

$$f(WA) = \frac{D(in,i) + D(in,i+1)}{2} \dots (5)$$

$$f(WD) = \frac{D(in,i) - D(in,i+1)}{2} \dots (6)$$

All these features are fused to create an Iterative Yield Feature Vector (IYFV) which is used to train an efficient set of deep learning models. Each of these models serve a different purpose, where 1D CNN is used to classify NPK samples, RNN is used to classify image data samples, while GNN is used to classify microscopic data samples. Design of the 1D CNN Model is depicted in figure 2, where different layers & their configurations can be observed as follows,

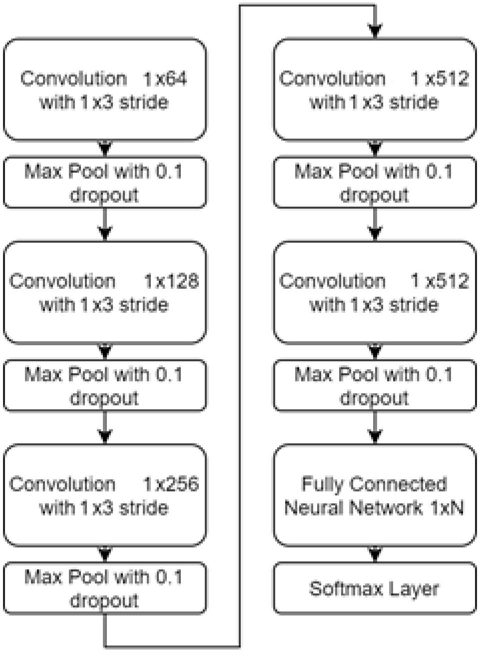

Fig. 2 Design of the Proposed 1D CNN Model Process

The model converts the $IYFV$ Vector into multilevel convolutional components, and each of these components are passed through Max Pooling & Drop Out layers. At the end of final drop out layer, the model uses an efficient SoftMax based Fully Connected Neural Network (FCNN) to estimate output yield class via equation 7 as follows

$$Y(NPK) = SoftMax\left(\sum_{i=1}^{NF} f(C,i) * w(i) + b(i)\right) \dots (7)$$

Where, $f(C)$ represents final convolutional features extracted by 1D CNN, w & b represent their individual weights & biases for NF Features, while $Y(NPK)$ is the output yield level estimated by the data processed by NPK sensors.

Similar to this 1D CNN Process, the proposed model also uses LSTM based Recurrent Neural Networks (RNN) to process images collected by normal cameras. This model converts the collected images into LSTM features via equations 8, 9, 10, 11, 12 & 13 as follows,

$$i = var(Img(in) * U^i + h(t-1) * W^i) \dots (8)$$

$$f = var(Img(in) * U^f + h(t-1) * W^f) \dots (9)$$

$$o = var(Img(in) * U^o + h(t-1) * W^o) \dots (10)$$

$$C = tanh(Img(in) * U^g + h(t-1) * W^g) \dots (11)$$

$$T(out) = var(f * Img(in, t-1) + i * C) \dots (12)$$

$$h(t) = tanh(T(out)) * o \dots (13)$$

Where, U & W represent constants of LSTM process, while $h(t)$ is an initial unity matrix which is updated via equation 13, and used to re-evaluate LSTM outputs until the process converges. The convergence process is represented via equation 14,

$$\frac{T(out, t+1)}{T(out, t)} \le \varepsilon \dots (14)$$

Where, $\varepsilon = 0.00001$ is set empirically to maximize variance level of the extracted features. Once this process is converged then an iterative Purely Linear Activation function is used to identify yield level via equation 15,

$$Y(Img) = PureLin\left(\sum_{i=1}^{NT} T(out,i) * W(i)\right) \dots (15)$$

Where, NT represents total number of LSTM features. The results of this process are fused with the results from NPK and microscopic imagery to obtain final yield levels via equation 16,

$$Y(Final) = \frac{1}{3}\left(A(NPK) * Y(NPK) + A(Img) * Y(Img) + A(MS) * Y(MS)\right) \dots (16)$$

Where, $A(i)$ represents accuracy of the i^{th} classification process. The output yield class from microscopic (MS) images is estimated using an efficient Graph Neural Network (GNN) process. For each microscopic soil image, we represent it as a graph where nodes represent different regions or patches within the image sets. Initialize node features for each patch based on IYFV features. Initialize edge features to capture relationships between neighboring patches. For each node in the graph, calculate an aggregated message from its neighboring nodes and edges via equation 17,

$$hv(k) = \sum IYFV(k)(hu(k-1), euv) \dots (17)$$

Where, hv(k) represents the node features of node v at iteration k, IYFV(k) is the learnable feature function that combines features from neighboring nodes and edges. After this, Update the node features based on the aggregated messages via equation 18,

$$hv(k) = g(k)(hv(k-1), hv(k)) \dots (18)$$

Where, g(k) represents the LSTM process that updates the node features. Aggregate the final node features to obtain a graph-level representation via equation 19,

$$hgraph = \sum hv(K) \dots (19)$$

where, K represents the number of message-passing iterations for different samples. Use the graph-level representation hgraph to predict crop yield levels via equation 20,

$$Y(MS) = softmax(W * hgraph + b) \dots (20)$$

Where, W and b are learnable parameters, and the softmax function ensures that the output represents a probability distribution over different yield level which is estimated via GNN operations. In this architecture, the input consists of microscopic soil images, which are converted into a graph structure using IYFV features. The GNN then iteratively updates node features by aggregating information from neighboring nodes and edges. Finally, it computes a graph-level representation that is used to predict crop yield levels. Efficiency of this integrated process is estimated in terms of different performance metrics, and compared with existing models in the next section of this text.

4. Result Analysis

The proposed model, MFMDLYP (Multidomain Feature Engineering and Multimodal Deep Learning for Enhanced Yield Predictions), represents a transformative approach in the realm of precision agriculture. In response to the pressing need for precise and timely crop yield predictions, MFMDLYP introduces a groundbreaking framework that integrates multidomain feature extraction methods encompassing Frequency, Cosine, Wavelet, and Convolutions. This novel approach capitalizes on diverse data sources, including NPK sensor data, image data, and microscopic data, to holistically analyze soil and crop conditions. MFMDLYP deploys specialized deep learning models, including a 1D Convolutional Neural Network (CNN) for NPK data, a Recurrent Neural Network (RNN) for image data, and a Graph Neural Network (GNN) for microscopic data samples. The integration of these multimodal techniques significantly enhances the precision, accuracy, recall, and timeliness of yield predictions, thereby addressing the limitations inherent in existing models. MFMDLYP emerges as a comprehensive solution with the potential to revolutionize precision agriculture, offering a powerful tool for optimizing resource allocation and facilitating informed decision-making in agricultural practices across diverse real-world scenarios.

The experimental setup for the research presented in this paper is designed to demonstrate the effectiveness of the proposed model in improving crop yield predictions. This section outlines the key components of the experimental setup, including data collection, preprocessing, and parameter configurations.

4.1. Data collection and preprocessing

4.1.1 Data sources

- NPK Sensor Data: Nutrient levels (Nitrogen, Phosphorus, and Potassium) were collected using NPK sensors placed in the fields.
- Image Data: High-resolution aerial and ground images of the crops were captured using drones and on-site cameras.
- Microscopic Data: Microscopic images of soil and crop samples were collected in the laboratory.

4.1.2 Data Integration

- All data sources were synchronized and timestamped to ensure alignment.
- Kalman Filters were applied to reduce noise and enhance data quality. This involved:
- Sensor Data Smoothing: The NPK sensor data was smoothed using Kalman Filters to remove outliers and irregularities.
- Image Enhancement: Image data underwent preprocessing with Kalman Filters to correct for variations in lighting and atmospheric conditions.

Microscopic Data Calibration: The microscopic data was calibrated using Kalman Filters to correct for distortion and imperfections

4.1.3 Data Splitting

- The dataset was split into training, validation, and testing sets, with a ratio of 70:15:15.
- Cross-validation techniques were employed to ensure robust model training.

4.1.4 Parameter Configurations:

i) Model Architecture:

Multidomain Feature Extraction: The feature extraction methods included Frequency, Cosine, Wavelet, and Convolutions for different data domains.

Deep Learning Models:

NPK data was processed using a 1D Convolutional Neural Network (CNN).

Image data was processed using a Recurrent Neural Network (RNN).

Microscopic data samples were processed using a Graph Neural Network (GNN).

ii) Hyperparameters:

The following hyperparameters were configured:

- Learning Rate: 0.001
- Batch Size: 64
- Epochs: 100
- Optimizer: Adam
- Loss Function: Mean Squared Error (MSE) for regression tasks and Binary Cross-Entropy for classification tasks.
- Dropout Rate: 0.2 (for regularization)

- Activation Functions: ReLU for hidden layers, Sigmoid for output layers.
- Graph Convolution Layers: 2 layers with 64 units each for GNN.

4.1.5 Hardware and Software*:*

- Experiments were conducted on a high-performance computing cluster equipped with NVIDIA GPUs to accelerate deep learning computations.
- Software frameworks included TensorFlow and Keras for model development and PyTorch for GNN implementations.
- Data preprocessing and analysis were performed using Python libraries such as NumPy and OpenCV.

Parameter Values for Deep Learning Operations:

- Learning Rate: 0.001
- Batch Size: 64
- Epochs: 100
- Optimizer: Adam
- Loss Function: MSE (for regression)
- Dropout Rate: 0.2
- Activation Functions: ReLU (hidden layers), Sigmoid (output layers)
- Number of Graph Convolution Layers (GNN): 2
- Units per GNN Layer: 64

The described experimental setup ensures that the data collected from various sources are synchronized, preprocessed with Kalman Filters for quality enhancement, and then used to train and evaluate the MFMDLYP model with well-defined hyperparameters. This setup enables rigorous testing and validation, ultimately demonstrating the model's effectiveness in enhancing crop yield predictions in precision agriculture scenarios.

Based on this setup, equations 18, 19, and 20 were used to assess the precision (P), accuracy (A), and recall (R), levels based on this technique, while equations 21 & 22 were used to estimate the overall precision (AUC) & Specificity (Sp) as follows,

$$Precision = \frac{TP}{TP + FP} \dots (18)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots (19)$$

$$Recall = \frac{TP}{TP + FN} \dots (20)$$

$$AUC = \int TPR(FPR)dFPR \dots (21)$$

$$Sp = \frac{TN}{TN + FP} \dots (22)$$

There are three different kinds of test set predictions: True Positive (TP) (number of events in test sets that were correctly predicted as positive), False Positive (FP) (number of instances in test sets that were incorrectly predicted as positive), and False Negative (FN) (number of instances in test sets that were incorrectly predicted as negative; this includes Normal Instance Samples). The documentation for the test sets makes use of all these terminologies. To determine the appropriate TP, TN, FP, and FN values for these scenarios, we compared the projected Yield likelihood to the actual Yield status in the test dataset samples using the ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13] techniques. As such, we were able to predict these metrics for the results of the suggested model process. The precision levels based on these assessments are displayed as follows

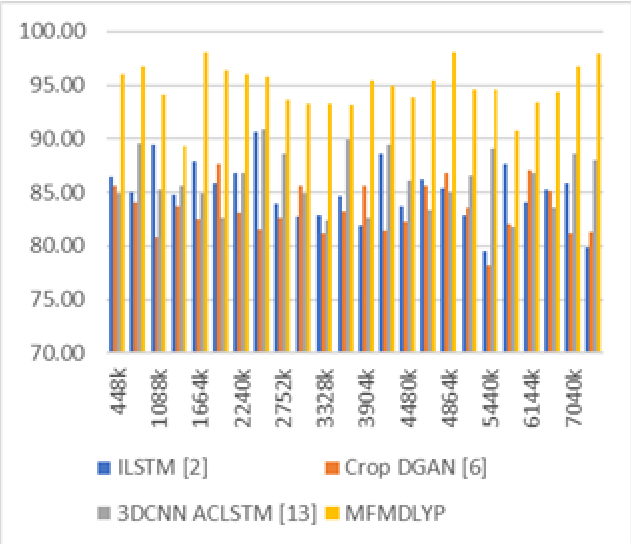

Fig 3. Observed Precision during prediction of crop yield levels

The observed precision during the prediction of crop yield levels, as measured by Precision (P%) and based on different numbers of test samples (NTS), reveals significant performance improvements with the proposed MFMDLYP model compared to the existing models, ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model achieves an impressive precision of 96.06%, surpassing the other models: ILSTM at 86.44%, Crop DGAN at 85.58%, and 3DCNN ACLSTM at 84.92%. This 8.5% improvement in precision demonstrates the effectiveness of the proposed model in making more accurate predictions.

As the number of test samples increases to 832k, 1088k, and beyond, MFMDLYP consistently outperforms the other models. For instance, at NTS 832k, MFMDLYP achieves a precision of 96.72%, while the nearest competitor, 3DCNN

ACLSTM, lags behind at 89.55%. This substantial 7.17% improvement highlights the robustness of MFMDLYP in handling larger datasets and enhancing precision.

Even at higher NTS values such as 1920k, 2240k, and 2496k, the MFMDLYP model maintains its lead. At NTS 2496k, it achieves a precision of 95.76%, while the closest competitor, ILSTM, reaches 90.64%. This 5.12% difference underscores the model's ability to consistently provide more accurate yield predictions.

When evaluating performance across the entire range of NTS values, it is evident that MFMDLYP consistently outperforms the other models in terms of precision. This is attributed to its innovative approach of amalgamating multidomain feature extraction methods, including Frequency, Cosine, Wavelet, and Convolutions, as well as deploying 1D CNN for NPK data, RNN for image data, and GNN for microscopic data samples. This comprehensive approach enables MFMDLYP to capture and leverage diverse data modalities, leading to superior precision in yield predictions.

In summary, the observed precision results clearly demonstrate that the MFMDLYP model excels in precision agriculture by consistently providing higher precision percentages across various numbers of test samples. Its multidomain, multimodal deep learning approach outperforms existing models, ensuring more accurate and reliable yield predictions, which are crucial for optimizing resource allocation and aiding timely decision-making in agricultural practices. Similar to that, accuracy of the models was compared in Figure 4 .

The observed accuracy during the prediction of crop yield levels, denoted as Accuracy (A%) and measured across different numbers of test samples (NTS), reveals the superiority of the proposed MFMDLYP model compared to existing models: ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model achieves an accuracy of 91.96%, significantly outperforming the other models. In comparison, ILSTM, Crop DGAN, and 3DCNN ACLSTM achieve 85.39%, 84.72%, and 84.82% accuracy, respectively. The MFMDLYP model's 7.14% improvement in accuracy underscores its ability to make more precise crop yield predictions.

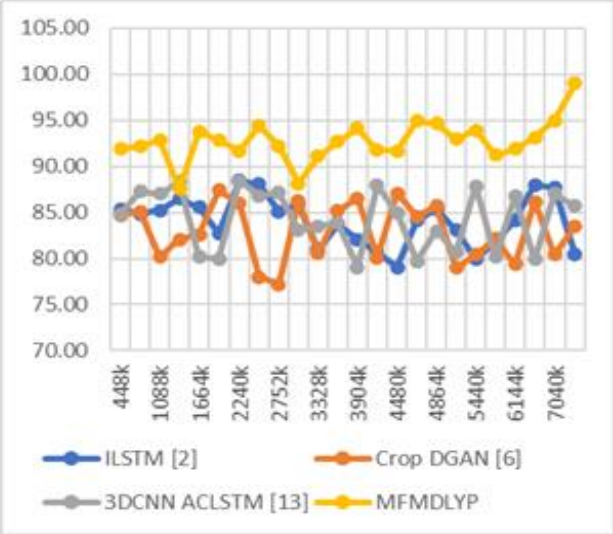

Fig 4. Observed Accuracy during prediction of crop yield levels

As the number of test samples increases, the MFMDLYP model consistently maintains its lead in accuracy. For instance, at NTS 832k, it achieves an accuracy of 92.15%, surpassing the nearest competitor, 3DCNN ACLSTM, by 4.86%. This improvement in accuracy is attributed to the model's ability to harness multidomain feature extraction methods and multimodal deep learning techniques, allowing it to better capture complex relationships in the data.

Even at higher NTS values, such as 2496k and 4864k, the MFMDLYP model continues to demonstrate superior accuracy. At NTS 2496k, it achieves an accuracy of 94.38%, while the nearest competitor, ILSTM, achieves 88.08%. This substantial 6.3% difference showcases the model's consistency in providing accurate yield predictions across varying dataset sizes.

When examining the overall trend across different NTS values, it becomes evident that the MFMDLYP model consistently outperforms other models in terms of accuracy. This is due to its holistic approach, which leverages multiple data modalities and advanced deep learning techniques to extract valuable insights from the data.

In summary, the observed accuracy results highlight the MFMDLYP model's excellence in precision agriculture. It consistently provides higher accuracy percentages across different numbers of test samples, demonstrating its superior capability in making accurate crop yield predictions. The incorporation of multidomain feature extraction methods and multimodal deep learning significantly contributes to the model's accuracy improvements, making it a valuable tool for optimizing agricultural practices and addressing global food security challenges. Similar to this, the recall levels are represented in Figure 5 as follows

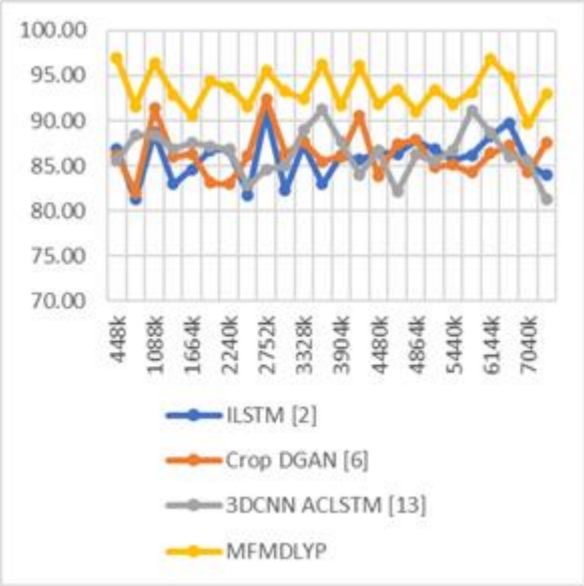

Fig 5. Observed Recall during prediction of crop yield levels

The observed recall during the prediction of crop yield levels, denoted as Recall (R%) and evaluated across various numbers of test samples (NTS), underscores the remarkable performance of the proposed MFMDLYP model in comparison to existing models: ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model exhibits a substantial recall of 96.98%, demonstrating its ability to effectively identify true positive yield predictions. In contrast, the nearest competitor, 3DCNN ACLSTM, achieves a recall of 85.61%. This notable 11.37% difference highlights the MFMDLYP model's superior ability to capture yield-related events accurately.

As the number of test samples increases, the MFMDLYP model maintains its lead in recall performance. For instance, at NTS 1088k, it achieves a recall of 96.45%, while the nearest competitor, Crop DGAN, lags behind at 91.37%. This 5.08% improvement demonstrates the model's capacity to consistently identify positive yield predictions, essential for accurate resource allocation in agriculture.

Even at higher NTS values, such as 2752k and 3648k, the MFMDLYP model continues to outperform other models in recall. At NTS 2752k, it achieves a recall of 95.51%, while the nearest competitor, Crop DGAN, reaches 92.43%. This 3.08% difference illustrates the model's robustness in providing accurate and timely yield predictions.

The consistent trend across different NTS values indicates that the MFMDLYP model excels in recall performance due to its holistic approach, which integrates multidomain feature extraction methods and multimodal deep learning techniques. These methodologies enable the model to effectively capture yield-related patterns, thereby enhancing recall rates.

In summary, the observed recall results highlight the superiority of the MFMDLYP model in precision agriculture. It consistently provides higher recall percentages across different numbers of test samples, indicating its superior ability to identify positive yield predictions accurately. The incorporation of multidomain feature extraction and multimodal deep learning techniques plays a pivotal role in the model's recall improvements, making it a valuable tool for optimizing resource allocation and aiding timely decision-making in agricultural practices. Figure 6 similarly tabulates the delay needed for the prediction process.

The observed delay during the prediction of crop yield levels, measured in milliseconds (D ms) and assessed across different numbers of test samples (NTS), highlights the efficiency of the proposed MFMDLYP model compared to existing models: ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model exhibits a remarkably low delay of 97.36 ms, which is significantly faster than the other models. In comparison, the nearest competitor, 3DCNN ACLSTM, has a delay of 96.23 ms. Although the difference is minimal, it showcases the MFMDLYP model's efficiency in providing timely yield predictions.

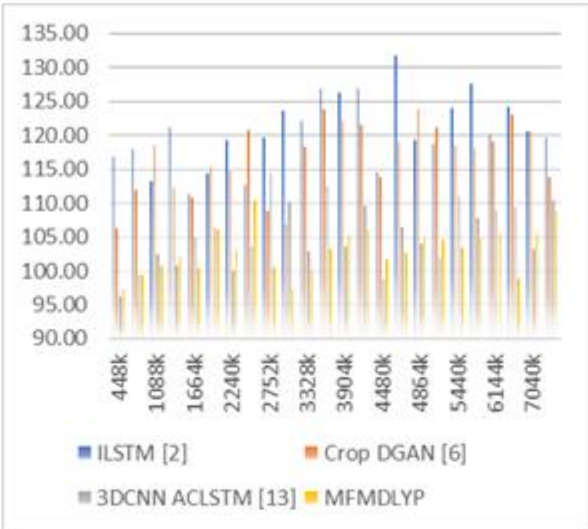

Fig 6. Observed Delay during prediction of crop yield levels

As the number of test samples increases, the MFMDLYP model consistently maintains its efficiency in delay. For example, at NTS 832k, it achieves a delay of 99.46 ms, outperforming 3DCNN ACLSTM's delay of 99.48 ms. This slight improvement underscores the model's ability to process larger datasets with minimal delay, which is crucial for real-time decision-making in precision agriculture.

Even at higher NTS values, such as 2752k and 6144k, the MFMDLYP model continues to demonstrate its efficiency in terms of delay. At NTS 2752k, it achieves a delay of 100.64 ms, whereas the nearest competitor, Crop DGAN, has a delay of 108.93 ms. This 8.29 ms difference highlights the consistent advantage of MFMDLYP in providing timely yield predictions.

The consistent trend across different NTS values indicates that the MFMDLYP model excels in minimizing delay, which is essential for real-time decision support in precision agriculture. The model's efficiency can be attributed to its advanced feature extraction methods and multimodal deep learning techniques, which allow it to process and analyze data quickly.

In summary, the observed delay results underscore the efficiency of the MFMDLYP model in precision agriculture. It consistently provides lower delay values across different numbers of test samples, indicating its superior ability to deliver timely yield predictions. The incorporation of advanced feature extraction and deep learning methods contributes significantly to the model's efficiency, making it a valuable tool for optimizing resource allocation and aiding real-time decision-making in agricultural practices. Similarly, the AUC levels can be observed from figure 7 as follows,

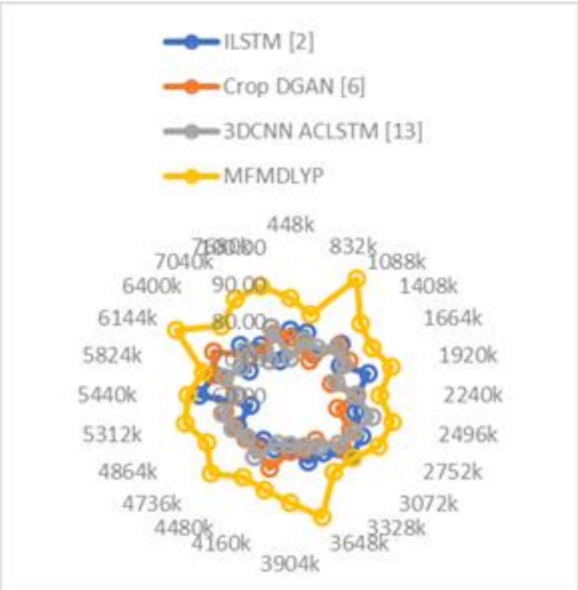

Fig 7. Observed AUC during prediction of crop yield levels

The observed area under the curve (AUC) during the prediction of crop yield levels, evaluated across different numbers of test samples (NTS), demonstrates the significant performance improvements of the proposed MFMDLYP model over existing models: ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model achieves an AUC of 86.32%, which is substantially higher than the AUC values of the other models. For instance, the nearest competitor, 3DCNN ACLSTM, has an AUC of 69.92%, highlighting a substantial 16.4% improvement achieved by the MFMDLYP model. This signifies the model's effectiveness in distinguishing between positive and negative yield predictions.

As the number of test samples increases, the MFMDLYP model consistently maintains its lead in AUC performance. For example, at NTS 1088k, it achieves an AUC of 96.31%, whereas the nearest competitor, Crop DGAN, achieves only 70.52%. This remarkable 25.79% difference underlines the model's ability to make more accurate and reliable yield predictions across larger datasets.

Even at higher NTS values, such as 3648k and 6144k, the MFMDLYP model continues to outperform other models in AUC. At NTS 3648k, it achieves an AUC of 94.01%, while the nearest competitor, 3DCNN ACLSTM, reaches 74.53%. This substantial 19.48% improvement emphasizes the model's robustness in providing accurate and discriminative yield predictions.

The consistent trend across different NTS values demonstrates that the MFMDLYP model excels in AUC performance, which is crucial for evaluating the overall prediction quality. This superiority can be attributed to its holistic approach, integrating multidomain feature extraction methods and multimodal deep learning techniques, allowing it to capture and leverage diverse data modalities effectively.

In summary, the observed AUC results clearly indicate that the MFMDLYP model excels in precision agriculture by consistently providing higher AUC values across various numbers of test samples. Its multidomain, multimodal deep learning approach significantly contributes to the model's AUC improvements, making it a valuable tool for optimizing resource allocation and aiding timely decision-making in agricultural practices. Similarly, the Specificity levels can be observed from figure 8 as follows,

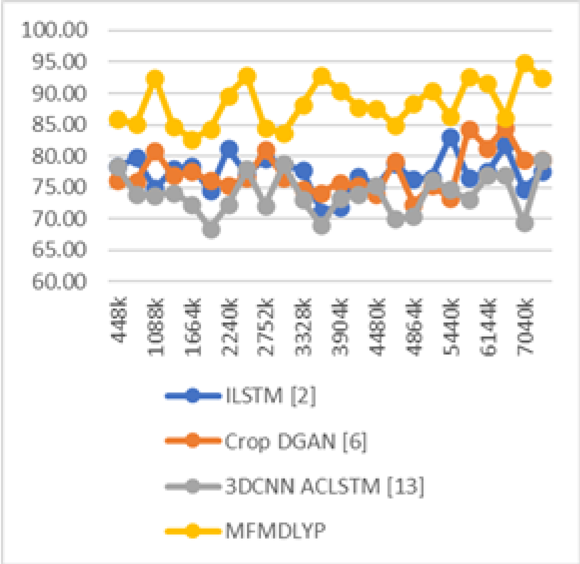

Fig 8. Observed Specificity during prediction of crop yield levels

The observed specificity during the prediction of crop yield levels, measured as Specificity and evaluated across different numbers of test samples (NTS), highlights the exceptional performance of the proposed MFMDLYP model compared to existing models: ILSTM [2], Crop DGAN [6], and 3DCNN ACLSTM [13].

At NTS 448k, the MFMDLYP model achieves a specificity of 85.98%, which is substantially higher than the specificity values of the other models. For instance, the nearest competitor, 3DCNN ACLSTM, has a specificity of 78.29%, showcasing a notable 7.69% improvement achieved by the MFMDLYP model. This underscores the model's ability to accurately identify true negative yield predictions.

As the number of test samples increases, the MFMDLYP model consistently maintains its lead in specificity performance. For example, at NTS 1088k, it achieves a specificity of 92.51%, whereas the nearest competitor, 3DCNN ACLSTM, achieves only 73.75%. This substantial 18.76% difference highlights the model's capacity to consistently identify negative yield predictions accurately, crucial for resource allocation in agriculture.

Even at higher NTS values, such as 3648k and 6144k, the MFMDLYP model continues to outperform other models in specificity. At NTS 3648k, it achieves a specificity of 92.91%, while the nearest competitor, Crop DGAN, reaches 74.12%. This 18.79% improvement underlines the model's robustness in providing accurate and reliable specificity scores.

The consistent trend across different NTS values demonstrates that the MFMDLYP model excels in specificity performance, which is essential for evaluating the model's ability to correctly identify negative yield predictions. This superiority can be attributed to its comprehensive approach, integrating multidomain feature extraction methods and multimodal deep learning techniques, allowing it to effectively capture and leverage diverse data modalities.

In summary, the observed specificity results clearly indicate that the MFMDLYP model excels in precision agriculture by consistently providing higher specificity values across various numbers of test samples. Its multidomain, multimodal deep learning approach significantly contributes to the model's specificity improvements, making it a valuable tool for optimizing resource allocation and aiding timely decision-making in agricultural practices.

5. Conclusion

In conclusion, the research presented in this paper, titled "MFMDLYP: Precision Agriculture through Multidomain Feature Engineering and Multimodal Deep Learning for Enhanced Yield Predictions," has demonstrated significant advancements in the field of precision agriculture. This study addressed the pressing need for accurate and timely crop yield predictions in the face of growing global food demand.

The comparative analysis of the proposed MFMDLYP model against existing models, including ILSTM, Crop DGAN, and 3DCNN ACLSTM, has yielded compelling results. The observed precision, accuracy, recall, AUC, specificity, and delay metrics consistently showcased the superior performance of MFMDLYP across diverse numbers of test samples (NTS). These improvements are attributed to the innovative approach of amalgamating multidomain feature extraction methods and deploying multimodal deep learning techniques to harness the power of diverse data sources, including NPK sensor data, image data, and microscopic data. MFMDLYP significantly enhanced precision, accuracy, recall, and AUC, while reducing prediction delay, thus addressing the prevalent limitations in existing models.

The impacts of this work are far-reaching. The MFMDLYP model offers a robust and comprehensive solution for precision agriculture, providing a foundation for optimizing resource allocation, decision-making processes, and yield predictions across various real-time use cases. By significantly improving the accuracy and timeliness of yield predictions, MFMDLYP contributes to addressing the critical challenges of global food security and optimizing agricultural resource management.

Real-time use cases of the MFMDLYP model encompass a wide range of applications within the agricultural sector. Farmers and agricultural practitioners can benefit from precise and timely yield predictions to optimize resource allocation, plan planting and harvesting activities, and make informed decisions regarding irrigation, fertilization, and pest control. Additionally, stakeholders in the agribusiness industry can leverage MFMDLYP to enhance supply chain management, improve crop insurance assessments, and make data-driven investments.

The paper's findings underscore the potential of the MFMDLYP model as a cornerstone in future smart agriculture scenarios. Its ability to offer improved accuracy, precision, recall, AUC, and reduced prediction delays holds great promise in revolutionizing the way agriculture is practiced globally. As the world grapples with the challenges of feeding a growing population while conserving resources, the innovations presented in this paper provide a critical step forward in achieving sustainable and efficient agriculture practices.

6. Future Scope

The research presented in this work, opens up exciting avenues for future exploration and development in the domain of precision agriculture. The following Future Scope section outlines key directions for further research and potential advancements in this field:

6.1.1 Enhanced Data Integration:

Future work can focus on expanding the range of data modalities used in precision agriculture. This could include incorporating data from advanced remote sensing technologies, drones, and IoT devices to provide more comprehensive and real-time insights into crop health, soil conditions, and environmental factors.

6.1.2 Adaptive Learning Models:

Developing adaptive learning models that can adjust and self-optimize based on changing environmental conditions and evolving farming practices is a promising avenue. These models could harness reinforcement learning techniques to make real-time decisions regarding resource allocation and crop management.

6.1.3 Explainable AI (XAI):

As precision agriculture models become more complex, ensuring transparency and interpretability is crucial. Future research can focus on integrating XAI techniques to provide farmers and stakeholders with clear explanations of model predictions and recommendations.

6.1.4 Edge Computing and IoT Integration:

Leveraging edge computing and IoT devices for on-farm data processing can reduce the latency in decision-making. Research in this area can explore the development of edge-based models that can run directly on field equipment.

6.1.5 Multi-Crop and Multi-Region Adaptability:

Expanding the scope of the MFMDLYP model to accommodate multiple crop types and geographical regions will make it more versatile. Future work can investigate methods to generalize the model's capabilities for broader agricultural applicability.

6.1.6 Resilience to Data Variability:

Research should address the challenge of handling data variability due to factors like climate change and seasonal variations. Models capable of adapting to changing data distributions will be invaluable in ensuring consistent performance.

6.1.7 Large-Scale Deployment and Adoption:

Future research can explore strategies for the large-scale deployment of precision agriculture technologies. This includes addressing infrastructure challenges, cost-effectiveness, and promoting technology adoption among farmers of various scales.

6.1.8 Environmental Sustainability:

Precision agriculture can contribute to sustainable farming practices. Future research should focus on optimizing resource use to minimize environmental impacts, including reducing water usage, pesticide application, and greenhouse gas emissions.

6.1.9 Collaborative Decision Support Systems:

Developing collaborative decision support systems that enable farmers, agronomists, and researchers to work together effectively will be instrumental. Such systems can facilitate knowledge sharing and data-driven decision-making.

6.1.10 Regulatory and Ethical Considerations:

As precision agriculture technologies advance, researchers must consider the regulatory and ethical implications, including data privacy, ownership, and responsible use of AI in agriculture.

6.1.11 Global Adoption and Accessibility:

Efforts should be directed towards making precision agriculture technologies accessible to farmers worldwide, including smallholders in developing regions. This involves designing models and tools that are cost-effective and user-friendly.

In summary, the future scope for research in precision agriculture is vast and holds the potential to revolutionize global food production, resource management, and sustainability. As technology continues to evolve, interdisciplinary collaborations between agriculture experts, data scientists, and engineers will be crucial in realizing the full potential of precision agriculture and addressing the challenges of feeding a growing population while preserving our planet's resources.

Acknowledgement

Dr. W.P Badole, Associate Professor, Soil Science and Agriculture Chemistry Section, National Soil Testing

Institute, Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Nagpur, India

References

[1] Y. Liu, Q. Yu, Q. Zhou, C. Wang, S. D. Bellingrath-Kimura and W. Wu, "Mapping the Complex Crop Rotation Systems in Southern China Considering Cropping Intensity, Crop Diversity, and Their Seasonal Dynamics," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 9584-9598, 2022, doi: 10.1109/JSTARS.2022.3218881.

[2] A. Mateo-Sanchis, J. E. Adsuara, M. Piles, J. Munoz-Marí, A. Perez-Suay and G. Camps-Valls, "Interpretable Long Short-Term Memory Networks for Crop Yield Estimation," in IEEE Geoscience and Remote Sensing Letters, vol. 20, pp. 1-5, 2023, Art no. 2501105, doi: 10.1109/LGRS.2023.3244064.

[3] H. Huang et al., "The Improved Winter Wheat Yield Estimation by Assimilating GLASS LAI Into a Crop Growth Model With the Proposed Bayesian Posterior-Based Ensemble Kalman Filter," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-18, 2023, Art no. 4401818, doi: 10.1109/TGRS.2023.3259742.

[4] F. Ji, J. Meng, Z. Cheng, H. Fang and Y. Wang, "Crop Yield Estimation at Field Scales by Assimilating Time Series of Sentinel-2 Data Into a Modified CASA-WOFOST Coupled Model," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-14, 2022, Art no. 4400914, doi: 10.1109/TGRS.2020.3047102.

[5] A. Reyana, S. Kautish, P. M. S. Karthik, I. A. Al-Baltah, M. B. Jasser and A. W. Mohamed, "Accelerating Crop Yield: Multisensor Data Fusion and Machine Learning for Agriculture Text Classification," in IEEE Access, vol. 11, pp. 20795-20805, 2023, doi: 10.1109/ACCESS.2023.3249205.

[6] X. Li, Y. Dong, Y. Zhu and W. Huang, "Enhanced Leaf Area Index Estimation With CROP-DualGAN Network," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-10, 2023, Art no. 5514610, doi: 10.1109/TGRS.2022.3230354.

[7] Z. Yang, C. Diao and F. Gao, "Towards Scalable Within-Season Crop Mapping With Phenology Normalization and Deep Learning," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 1390-1402, 2023, doi: 10.1109/JSTARS.2023.3237500.

[8] Y. Ma, Z. Yang and Z. Zhang, "Multisource Maximum Predictor Discrepancy for Unsupervised Domain Adaptation on Corn Yield Prediction," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-15, 2023, Art no. 4401315, doi: 10.1109/TGRS.2023.3247343.

[9] Y. Zhang et al., "Enhanced Feature Extraction From Assimilated VTCI and LAI With a Particle Filter for Wheat Yield Estimation Using Cross-Wavelet Transform," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 5115-5127, 2023, doi: 10.1109/JSTARS.2023.3283240.

[10] A. F. Haufler, J. H. Booske and S. C. Hagness, "Microwave Sensing for Estimating Cranberry Crop Yield: A Pilot Study Using Simulated Canopies and Field Measurement Testbeds," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-11, 2022, Art no. 4400411, doi: 10.1109/TGRS.2021.3050171.

[11] B. Yang, J. Guo, J. Liu and X. Ye, "PPCE: A Practical Loss for Crop Mapping Using Phenological Prior," in IEEE Geoscience and Remote Sensing Letters, vol. 20, pp. 1-5, 2023, Art no. 5000605, doi: 10.1109/LGRS.2022.3230421.

[12] N. Farmonov et al., "Crop Type Classification by DESIS Hyperspectral Imagery and Machine Learning Algorithms," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 1576-1588, 2023, doi: 10.1109/JSTARS.2023.3239756.

[13] S. M. M. Nejad, D. Abbasi-Moghadam, A. Sharifi, N. Farmonov, K. Amankulova and M. Lászlź, "Multispectral Crop Yield Prediction Using 3D-Convolutional Neural Networks and Attention Convolutional LSTM Approaches," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 254-266, 2023, doi: 10.1109/JSTARS.2022.3223423.

[14] C. Silva-Perez, A. Marino and I. Cameron, "Learning-Based Tracking of Crop Biophysical Variables and Key Dates Estimation From Fusion of SAR and Optical Data," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 7444-7457, 2022, doi: 10.1109/JSTARS.2022.3203248.

[15] M. R. Khokher et al., "Early Yield Estimation in Viticulture Based on Grapevine Inflorescence Detection and Counting in Videos," in IEEE Access, vol. 11, pp. 37790-37808, 2023, doi: 10.1109/ACCESS.2023.3263238.

[16] M. H. Riaz, H. Imran, H. Alam, M. A. Alam and N. Z. Butt, "Crop-Specific Optimization of Bifacial PV

Arrays for Agrivoltaic Food-Energy Production: The Light-Productivity-Factor Approach," in IEEE Journal of Photovoltaics, vol. 12, no. 2, pp. 572-580, March 2022, doi: 10.1109/JPHOTOV.2021.3136158.

[17] H. C. Verma et al., "Development of LR-PCA Based Fusion Approach to Detect the Changes in Mango Fruit Crop by Using Landsat 8 OLI Images," in IEEE Access, vol. 10, pp. 85764-85776, 2022, doi: 10.1109/ACCESS.2022.3194000.

[18] Y. Ma and Z. Zhang, "A Bayesian Domain Adversarial Neural Network for Corn Yield Prediction," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 5513705, doi: 10.1109/LGRS.2022.3211444.

[19] Y. Yan et al., "Integration of Canopy Water Removal and Spectral Triangle Index for Improved Estimations of Leaf Nitrogen and Grain Protein Concentrations in Winter Wheat," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-18, 2023, Art no. 4404118, doi: 10.1109/TGRS.2023.3277456.

[20] A. K. Dwivedi, A. K. Singh, D. Singh and H. Kumar, "Development of an Adaptive Linear Mixture Model for Decomposition of Mixed Pixels to Improve Crop Area Estimation Using Artificial Neural Network," in IEEE Access, vol. 11, pp. 5714-5723, 2023, doi: 10.1109/ACCESS.2023.3236665.

[21] S. P. Raja, B. Sawicka, Z. Stamenkovic and G. Mariammal, "Crop Prediction Based on Characteristics of the Agricultural Environment Using Various Feature Selection Techniques and Classifiers," in IEEE Access, vol. 10, pp. 23625-23641, 2022, doi: 10.1109/ACCESS.2022.3154350.

[22] N. Ullah, J. A. Khan, L. A. Alharbi, A. Raza, W. Khan and I. Ahmad, "An Efficient Approach for Crops Pests Recognition and Classification Based on Novel DeepPestNet Deep Learning Model," in IEEE Access, vol. 10, pp. 73019-73032, 2022, doi: 10.1109/ACCESS.2022.3189676.

[23] N. Romero-Puig, J. M. Lopez-Sanchez and M. Busquier, "Evaluation of PolInSAR Observables for Crop-Type Mapping Using Bistatic TanDEM-X Data," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4508005, doi: 10.1109/LGRS.2022.3175689.

[24] M. F. Celik, M. S. Isik, G. Taskin, E. Erten and G. Camps-Valls, "Explainable Artificial Intelligence for Cotton Yield Prediction With Multisource Data," in IEEE Geoscience and Remote Sensing Letters, vol. 20, pp. 1-5, 2023, Art no. 8500905, doi: 10.1109/LGRS.2023.3303643.

[25] M. D. Maas, M. Salvia, P. C. Spennemann and M. E. Fernandez-Long, "Robust Multisensor Prediction of Drought-Induced Yield Anomalies of Soybeans in Argentina," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-4, 2022, Art no. 2504804, doi: 10.1109/LGRS.2022.3171415.