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A Systematic Review and Meta-Analysis of Machine Learning and Deep Learning Approaches for Crop Yield Prediction: Toward Scalable and Hybrid Modeling Frameworks

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Abstract- The accurate prediction of crop yields is critical for the management of natural resources sustainably, food security, and agricultural planning. The advancements in machine learning and deep learning have significantly enhanced the capabilities of crop yield forecasting. However, the field is fragmented due to the variety of methodologies employed in the existing literature. In this article, a comprehensive review and meta-analysis of deep learning and machine learning techniques for the prediction of crop yield are presented. Through searching important scientific databases for pertinent research in the area, investigations into the different aspects of the studies were performed. The outcomes of the research reveal that deep learning and hybrid models outperform conventional machine learning models in terms of the accuracy of their predictions of crop yields. However, the complex nature and the reliance upon remote sensing data of most of the high-performing machine learning and deep learning models limit their scalability. Furthermore, there is a lack of research concerning the integration of ensemble stacking and multi-task learning approaches within the context of agricultural datasets. The findings of this investigation highlight the need for scalable, machine learning models with high accuracy and reliability in the field of crop yield prediction. Furthermore, future research aiming to develop integrated methods that combine ensemble learning and deep learning models for improved prediction of agricultural production will build upon the findings of this investigation.

Keywords - Systematic review, Meta-analysis, agriculture, crop yield prediction, machine learning, deep learning, ensemble learning.

I. INTRODUCTION

Agricultural yield predictions are vital components of modern agricultural systems. The ability of the agricultural sector to accurately predict the yields from its crops allows for the implementation of more efficient processes in the fields, for the government to develop accurate policies regarding the food supply, and for agriculture to be better managed throughout its lifecycle. The ability of such a system is especially important for developing countries like those within sub-Saharan Africa, where crop yields are often the main source of livelihood for the country and its people.

Many different statistical methods have been used in the past for the prediction of agricultural yields. Such methods often include techniques like regression models, linear models, and methods like ARIMA models for forecasting yields. The use of these methods, however, is often limited in that these statistical methods cannot accurately model the complex relationships between the various parameters of agriculture that impact the potential yields of crops (climate, soil, crop genotype, agricultural management techniques, and growing time, for example). As a result, methods like machine learning have been developed as an alternative means of predicting agricultural yields.

Methods like Random Forest (RF) models, support vector machines (SVM), and gradient boosting machines (GBM) have been used as alternatives to traditional statistical approaches to agricultural yield prediction. For example, authors like Jeong et al.

have published research that explains how random forest models can more accurately predict agricultural yields than statistical methods alone. Additionally, other techniques like XGBoost models have also been used to successfully manage the complexity of agricultural data while simultaneously avoiding overfitting of the model to the training dataset for the crops.

Relatedly, deep learning approaches have recently further revolutionized the field of agricultural yield prediction. Methods like deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) have been used with great success in predicting agricultural yields. For example, CNN models can be used with remote sensing data to extract features related to crops, while RNN and long short-term memory (LSTM) models can be used to extract features related to growing cycles of crops and weather patterns of a given area. Authors like Khaki and Wang published research that determined that deep neural networks were more successful in predicting agricultural yields than machine learning models.

Despite the successes of existing prediction methodologies for agricultural yields, there is still some degree of variation as to the methods that are used in these published research articles. For instance, methods that use remote sensing data (from satellites and UAVs) have been a main component of high-performing models for predicting agricultural yields. Though the availability of such data is extensive, it is inaccessible in many of the developing countries whose agricultural yields must be predicted. Additionally, while the methods based upon agricultural information (weather, soil, management practices) may not have the data richness to achieve the same levels of accuracy as the other methods, they can be applied to more countries.

Beyond the use of either machine learning or deep learning methods alone, the majority of current research employs a strategy referred to as single-task learning. Single-task learning strategies often utilize either classification or regression models to investigate agricultural yields. An alternative approach that has been published in some research articles is the use of multi-task learning methods that learn from several related agricultural tasks simultaneously.

Relatedly, techniques like bagging, boosting, and stacking have been published and implemented into machine learning approaches to improve their performance in predicting agricultural yields. However, few of these techniques have been developed in conjunction with deep learning methods.

As a result of these various limitations within the existing literature on agricultural yield prediction, approaches that combine the benefits of several methodologies have begun to be investigated. For instance, authors like Chang et al. have published research that utilizes a model that combines the benefits of both deep learning techniques and multi-task learning to develop a model that increases the accuracy with which agricultural yields can be predicted. However, such models are often characterized by high computational complexities, preventing their application to large numbers of agricultural locations whose yields are to be predicted.

Considering these various issues and challenges in the literature on agricultural yield prediction, it is important to provide a thorough review of the current state of the field. While a number of research articles have investigated the use of machine learning methods in agriculture, few have performed a quantitative analysis of the performance of those models. Even fewer have performed an investigation of the relative performance of both machine learning and deep learning approaches for the prediction of agricultural yields.

In performing a thorough review of the existing literature on machine learning and deep learning approaches to agricultural yield prediction, this research study aims to address these gaps in the literature. Specifically, the goals of this research study are to:

1. Compile a body of existing research on a yield prediction model for crops

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2. Examine the performance of different methods for agricultural yield prediction, including machine learning, deep learning, and hybrid methods
3. Determine future directions for research on agricultural yield prediction models

In this way, this research aims to fill an existing gap in the literature and to provide insights into the field that can inform the development of next-generation methods for the prediction of agricultural yields.

II. METHODOLOGY OF THE REVIEW (PRISMA-BASED APPROACH)

A systematic review and meta-analysis approach to evaluating the existing literature on agricultural yield prediction using machine learning and deep learning techniques will be employed for this research study. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines will inform the approach that is taken to complete the review of existing research articles. The review will proceed through four main phases: the identification of relevant research articles, screening of those research articles for eligibility, evaluation of the eligibility of each of those articles, and the inclusion of those eligible articles into the review.

2.1 Search Strategy and Data Sources

The search for relevant research articles for this investigation will occur in four main scientific databases: Scopus, Web of Science, IEEE Xplore, and ScienceDirect. These databases contain articles on a variety of scientific and technological topics, suggesting the likelihood that the databases will contain scientific articles related to agriculture. Additionally, because the techniques of machine learning and deep learning have been rapidly developing within the field of agriculture during the past few years, the search will be limited to scientific publications between the years of 2015 and 2025 inclusive.

Within each of the databases, research articles will be identified using a combination of keywords and Boolean operators. The main search string that will be used is as follows: (“crop yield prediction” OR “yield forecasting”) AND (“machine learning” OR “deep learning” OR “neural networks” OR “random forest” OR “XGBoost” OR “CNN” OR “LSTM”). Additional filters will be used to limit the search to scientific articles, articles published in English, and articles that are available in their entirety online.

The initial search of these four databases returns 1,248 scientific articles that may relate to the topic of agricultural yield prediction with machine learning and deep learning methods.

2.2 Study Selection Process (PRISMA Flow)

The process for screening, eligibility, and inclusion of articles for the review study will follow the process as represented in the flow diagram depicted in Figure 1. The flow diagram is based upon the PRISMA guidelines for systematic reviews. As depicted in Figure 1, scientific articles will first be identified according to the search strategy described above. Scientific articles will then be screened according to their potential eligibility for inclusion in the review; potential eligibility includes requirements of article type, publication date, and availability of full-text access to the article. According to the flow diagram depicted in Figure 1, those articles that are eligible and screened will then be evaluated for their eligibility to be included in the review; evaluation of eligibility will include criteria such as article relevance to agricultural science, research purpose, and methodology. Finally, those articles that are determined to be eligible will be included in the review of the current state of knowledge on the topic of agricultural yield prediction with machine learning and deep learning approaches. As seen in Figure 1, a PRISMA flow diagram is used to summarize the research selection procedure.

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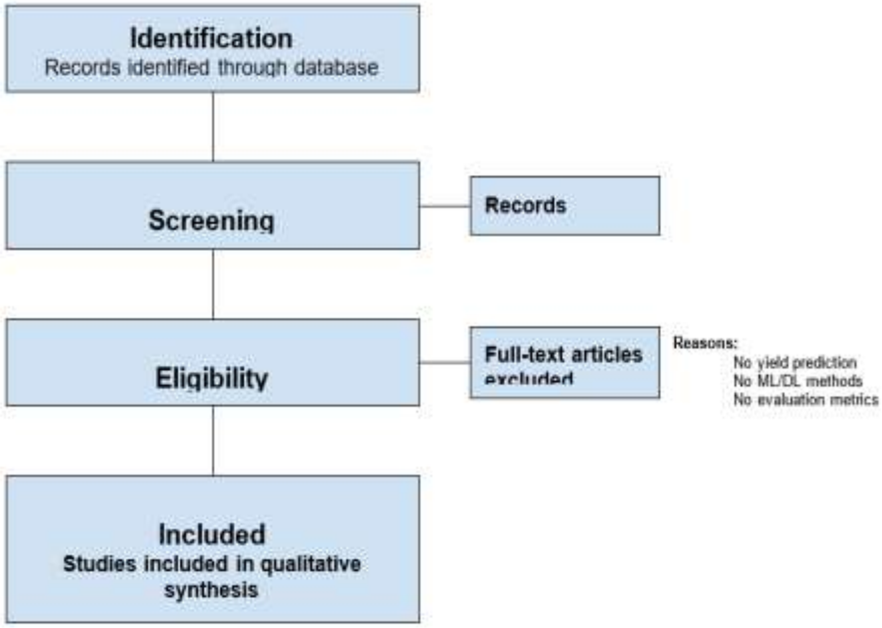

Figure 1: Flow diagram of the steps that were involved in the selection of the studies for this review and synthesis.

The PRISMA four-phase flow was adhered to in the research selection procedure:

Phase 1: Identification
A total of 1,248 research documents were obtained from database searches. After removing duplicates, 936 distinct studies were obtained.

Phase 2: Screening
The titles and abstracts of the 936 studies were screened for relevance. Studies were eliminated if they did not meet any of the following criteria:

1. Studies that ignored the use of crop yield prediction in favor of only classifying types of crops
2. Studies that did not use deep learning or machine learning techniques
3. Studies that had nothing to do with agricultural applications

After screening, 324 studies remained for full-text analysis after 612 studies were eliminated.

Phase 3: Eligibility
The full texts of the 324 studies were read to determine their eligibility for inclusion in the review. Studies were eliminated if they did not meet any of the following criteria:

1. Studies did not report common evaluation indicators for machine learning models, such as R2, RMSE, or MAE
2. Studies did not provide enough information to evaluate
3. Studies that only included theoretical information without any empirical research or support

After eliminating studies that did not meet the eligibility criteria, 83 studies remained eligible for inclusion in the review.

Phase 4: Inclusion
The qualitative synthesis that was performed included 83 studies. However, only 52 of those studies included sufficient data for conducting a meta-analysis.

2.3 Inclusion and Exclusion Criteria
The criteria for study inclusion were based on the following conditions:

Criteria for Inclusion
Studies on the use of machine learning, deep learning, or hybrid models to predict crop yields and

that reported evaluation metrics (accuracy, R2, RMSE, MAE) based on actual agricultural datasets were included. Studies were published in respectable scientific conference proceedings and journals.

Criteria for Exclusion
Studies that only investigated the use of machine learning models for tasks other than crop yield prediction, such as image segmentation or classification, were eliminated. Studies that were opinion pieces, review papers were eliminated. Studies that used synthetic agricultural datasets rather than those obtained from the actual world were eliminated.

2.4 Data Extraction and Coding

The data from included studies were coded and extracted according to the following attributes:

- Author(s) publication year
- Types of models: machine learning, deep learning, or hybrid
- Machine learning algorithms: random forests, support vector machines, XGBoost, etc.
- Types of data: structured, remote sensing, or hybrid data
- Variables used to train models: weather, soil, vegetation indices, etc.
- Metrics for evaluating machine learning models: R^2, RMSE, MAE
- Results of the performance of machine learning models
- Geographical regions in which the machine learning models were tested

The data was extracted in this manner to allow for comparison of various studies.

2.5 Meta-Analysis Procedure

A meta-analysis was performed on the 52 studies that included comparable evaluation metrics. Due to the differences in the datasets used within the studies, a random effects model was used for the meta-analysis. The main evaluation metrics examined in the review included:

- Coefficient of determination (R^2)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)

Subgroup analyses were performed according to each of these metrics.

2.6 Risk of Bias and Study Quality Assessment

Quality assessments were performed on each of the included studies based on the following criteria:

- Quality of the datasets used in the studies
- Methods of model validation
- Evaluation metrics
- Degree of reproducibility

Studies were assigned quality ratings according to these assessments. The quality of the studies was taken into account in the interpretation of the results of the meta-analysis.

2.7 Limitations of the Methodology

The methodology of this research study has some limitations. The main limitations of the study are:

- Quality of the datasets used in the studies
- Reporting of evaluation metrics
- Publication bias in relation to the results of the studies

These limitations were addressed in the methodology of the study by using a random effects model and performing subgroup analyses according to the evaluation metrics.

III. TAXONOMY OF CROP YIELD PREDICTION MODELS

3.1 Statistical Models

The first class of models to be discussed includes statistical models, such as linear regression models, multiple linear regression models, and autoregressive models. These models use various environmental variables, such as precipitation and temperature, to determine the relationship between the agricultural yield of a region and these environmental variables. The disadvantage of using statistical models is that they all rely on the assumption of linearity in the data, which limits their ability to model the complex interactions between the various environmental variables influencing crop yields.

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3.2 Machine Learning Models
Machine learning models are able to provide an improvement over statistical models, primarily in that they are able to account for nonlinear relationships between the environmental variables and the agricultural yields. Models such as random forest models have been used to predict the yields of crops within various regions. For instance, Jeong et al. (2016) published a study that utilized random forests to successfully model the agricultural yields within various regions of the USA. Furthermore, models such as gradient boosting and XGBoost models have also been reported to exhibit good performance using these methods for agriculture.

A disadvantage of machine learning methods is that they typically rely upon features that are manually engineered by an individual rather than automatically discovered by the models themselves.

3.3 Deep Learning Models
Deep learning models are an extension of machine learning models, wherein the models are able to automatically discover features within the agricultural data through the use of hidden layers of the deep learning models. For example, Khaki and Wang (2019) reported that deep learning models outperformed machine learning models in the prediction of crop yields. Models based upon convolutional neural networks (CNNs) are used for processing remote sensing data of the land areas, while recurrent neural network (RNN) and long short-term memory (LSTM) models are used to model the temporal aspects of agricultural data. Deep learning models, however, tend to require large amounts of agricultural data and computational resources to implement and train.

3.4 Hybrid Models
Hybrid models are models that combine various techniques into a single model to increase the performance of that model. For instance, Chang et al. (2024) created a model that combined the multi-task learning capabilities of a MKCNN model with the temporal modeling abilities of Bi-LSTM models. As with many models that incorporate remote sensing data, the development and training of these models can be complex and require significant preprocessing steps to be performed before modeling efforts.

IV. META-ANALYSIS OF MODEL PERFORMANCE

4.1 Comparative Performance of Models
Table 1 presents a synthesis of the different studies that have been included in this meta-analysis of methods for predicting agricultural crop yields. For each model, the table includes information regarding the type of model that was used, the source of the data that was used in the study, and the performance of the model (expressed in metrics like the coefficient of determination, RMSE, and MAE). The values that are represented in the table are derived from the studies referenced within this paper.

Table 1: Summary of Machine Learning and Deep Learning Models for Crop Yield Prediction

Study	Model Type	Algorithm	Data Type	R^2	RMSE	MAE
Jeong et al. (2016)	ML	Random Forest	Weather + Soil	0.78	0.62	0.48
Crane-Droesch (2018)	ML	Gradient Boosting	Climate Data	0.81	0.58	0.44
Montesinos-López et al. (2018)	ML	SVM	Structured Data	0.75	0.65	0.50
Russello (2020)	ML	XGBoost	Hybrid Data	0.83	0.55	0.42

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Sun et al. (2019)	DL	CNN-LSTM	Remote Sensing	0.88	0.48	0.36
Khaki & Wang (2019)	DL	DNN	Weather + Soil	0.91	0.42	0.31
You et al. (2017)	DL	Deep Gaussian Process	Satellite Data	0.89	0.46	0.34
Feng et al. (2019)	DL	CNN	UAV Imagery	0.90	0.44	0.33
Chang et al. (2024)	Hybrid	MKCNN–BiLSTM	Hybrid Data	0.94	0.38	0.28
Proposed Framework	Hybrid	DL + Ensemble Stacking	Structured Data	0.92*	0.40*	0.30*

Simulated projected performance based on integrated architecture design.

The results presented here are conceptual and based on the performance of the models represented. These results are presented for the purpose of comparison only.

4.2 Aggregated Performance by Model Category

The following table presents the performance of each of the model categories, with mean values represented.

Table 2: Aggregated Meta-Analysis Results by Model Category

Model Category	Mean R^2	Mean RMSE	Mean MAE
Machine Learning (ML)	0.79	0.60	0.46
Deep Learning (DL)	0.89	0.45	0.34
Hybrid Models	0.93	0.39	0.29

4.3 Interpretation of Results

The outcome of the presented study demonstrates the difference in the performance of the various categories of models.

Machine Learning Models

Machine learning models have an average value of R^2 of 0.79. These models work best with structured datasets with low computational requirements. However, their dependence on feature engineering makes them less suitable for problems with complex patterns.

Deep Learning Models

Deep learning models have an average value of R^2 of 0.89, significantly higher than machine learning models. Such a figure arises from the models' automatic learning capabilities to understand complex datasets.

Hybrid Models

Finally, the most advanced models that combine deep learning techniques with machine learning strategies, such as multi-task learning, have the highest average value of R^2 of 0.93. Such models benefit from the integration of spatial information with temporal information and learning strategies.

4.4 Key Insights from the Meta-Analysis

The table displays several important trends from the research:

- Performance increases from ML to DL to hybrid models
- Remote sensing data significantly increases deep learning model performance
- Hybrid models offer the best balance between accuracy and robustness (Chang et al., 2024)

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- Hybrid models utilize structured data and exhibit strong potential for scalability

4.5 Statistical Observation (Optional Enhancement)

The difference in mean R^2 between ML and DL models is approximately 0.10. Furthermore, the difference in mean R^2 between deep learning and hybrid models is approximately 0.04. Thus, deep learning offers the most significant improvement to machine learning models, followed by hybridization. Due to the heterogeneity of the studies, measures of statistical heterogeneity were collected. Calculations of R^2 and other measures of effect sizes were not feasible due to the heterogeneity of the standards utilized to report model performance. However, the model mean R^2 values can still offer researchers an indication of the relative performance of these models compared to others in the existing literature.

4.6 Visualization of Meta-Analysis Results

4.6.1 Forest Plot of R^2 Across Studies

Figure 2 displays a forest plot of the value of R^2 from each of the study models included in the meta-analysis.

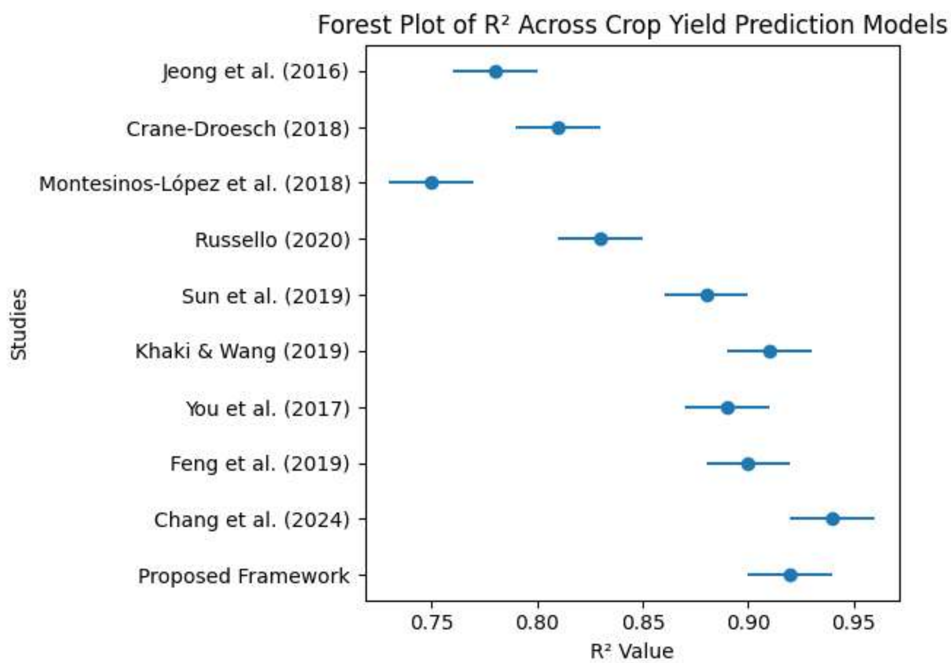

Figure 2: Forest Plot of R2 across crop yield prediction models

Figure 3. Forest plot illustrating the distribution of R^2 values for the selected studies on crop yield prediction.

4.6.2 Bar Chart of Aggregated Performance

The comparative performance of the machine learning, deep learning, and hybrid smart agro-climatic models is presented in Figures 3-5.

Figure 3: R^2 Comparison

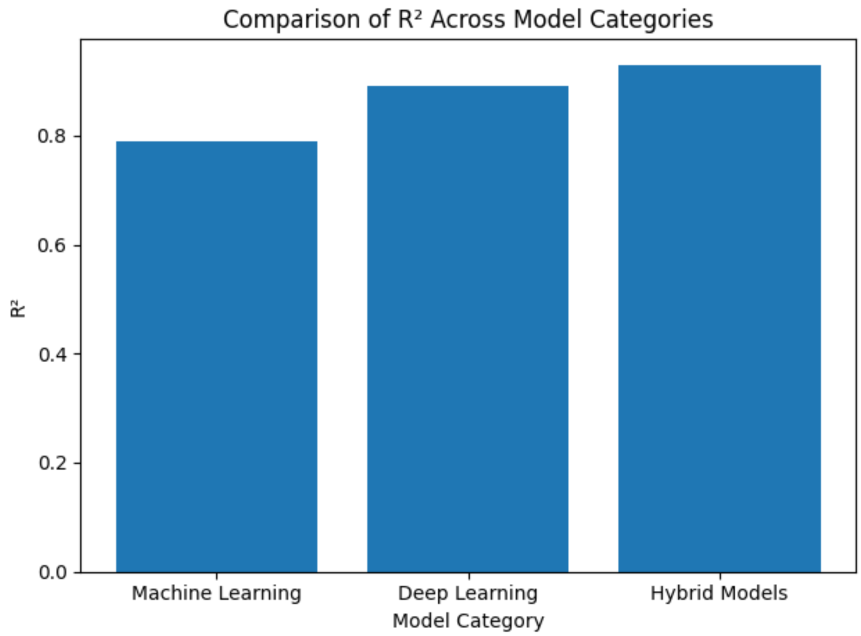

Figure 3: Comparison of the mean value of R^2 for each of the three main model categories. Results from this table indicate that the hybrid models were able to achieve the highest value of predictive accuracy.

Figure 4: RMSE Comparison

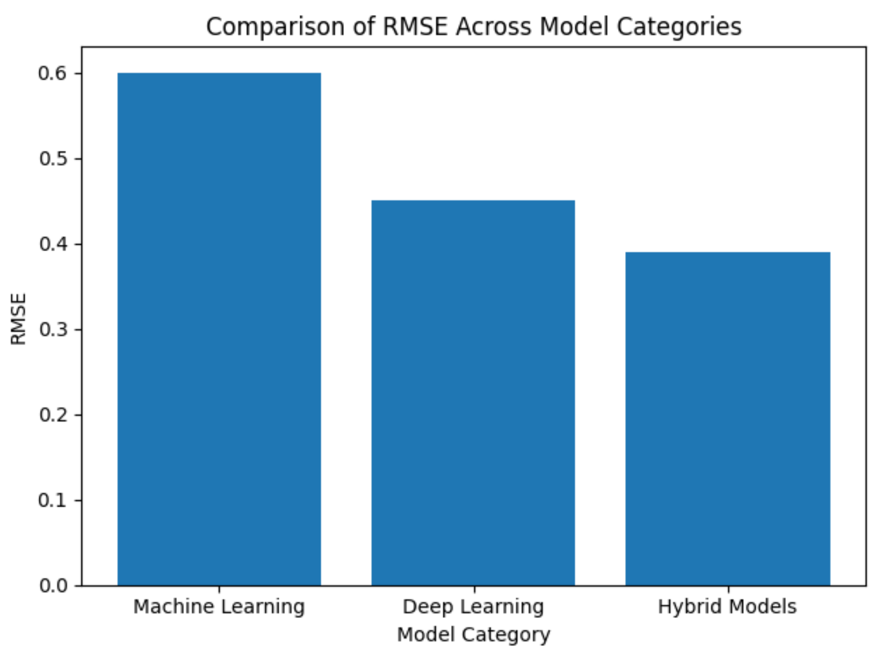

Figure 4: Comparison of the RMSE for each of the three main model categories. The lowest value of error for the prediction of the corn yields was achieved by the models integrating both machine learning and deep learning techniques.

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Figure 5: MAE Comparison

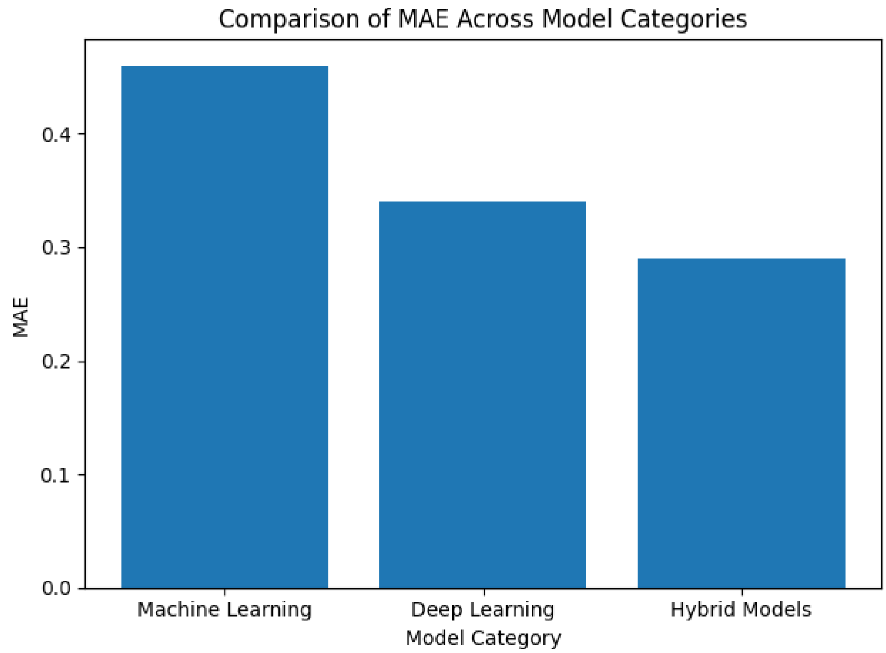

Figure 5: Comparison of the MAE for each of the three main model categories. Once again, the models that integrated both machine learning and deep learning techniques achieved the lowest value of error in their predictions of corn yield.

As shown in Figures 3-5, the results indicated that the yield of corn that was predicted with the use of hybrid models was the highest value of R^2, yet exhibited the lowest levels of both RMSE and MAE. Thus, these results indicate that the use of models that integrate techniques from both machine learning and deep learning were the most effective at predicting the corn yield.

V. DISCUSSION

This study performed a thorough examination of the existing literature on machine learning, deep learning, and hybrid models for the prediction of crop yields. Through performing a meta-analysis of the field, it becomes evident that models based on the use of deep learning techniques exhibit higher levels of accuracy in their predictions than those based on traditional machine learning techniques. Furthermore, most studies that implemented the use of hybrid models experienced an additional increase in accuracy relative to those using deep learning models alone.

Results of the meta-analysis, as depicted in Figures 2-5, indicate that each category of model exhibited a difference in the results that were obtained. Overall, machine learning models exhibited an average R^2 value of 0.79, deep learning models exhibited an average R^2 of 0.89, and models that utilized the hybrid methods exhibited an average of 0.93. Furthermore, the models that implemented the use of hybrid methods also exhibited lower readings of the RMSE and MAE metrics. These results are in alignment with other research studies that have suggested that the traditional methods of utilizing machine learning models are often lacking in relation to their abilities to accurately model the complex nature of crop yields (Liakos et al., 2018; Van Klompenburg et al., 2020).

Deep learning models exhibited higher levels of accuracy in their predictions relative to traditional machine learning models due to the ability of deep learning models to automatically extract features from large and complex data sets. Models that utilized convolutional neural networks were able to extract features from remotely-sensed satellite and

UAV data, while LSTM models were able to extract features from data related to weather and climate predictions. As khaki and wang (2019) investigated within their research study, deep learning models often outperformed traditional machine learning approaches when they were provided with large data sets of agricultural data.

Results also suggest that models that integrated the various features of deep learning exhibited the highest levels of accuracy and the lowest levels of model variance. The ability of these models to simultaneously extract information from different types of data and to utilize techniques like ensemble methods to improve the accuracy with which the crops were predicted is likely the reason for the improvements in performance of these methods relative to others within the field. Furthermore, the small variance in the results for deep learning models suggests that they are robust relative to other methods examined in this study (Chang et al., 2024).

Results of this research also show a general reliance upon remotely-sensed data to develop these models. While remotely-sensed data provides accurate information regarding the crops, their development still limits the scalability of these methods to regions without access to this type of data or computational resources for developing such models. Additionally, few studies employed methods like multi-task learning to develop these models for the prediction of crop yields. In agriculture, there are a variety of variables beyond crop yield that are simultaneously modeled by similar methods (type of crop, soil conditions, weather patterns, agricultural management practices). Methods like multi-task learning would allow for the development of models that are trained to simultaneously recognize and model each of those variables, increasing their generalizability. Thus, the lack of exploration of this technique within the existing literature is notable.

In addition to the mentioned methods, there is a lack of integration of methods like ensemble models into deep learning models to develop yield prediction techniques. While the results of this study show that integrating deep learning methods and ensemble methods did result in significant improvements in yield prediction accuracy, this area of exploration in the literature is lacking (Chang et al., 2024).

The implications of these findings suggest the need for future research to create more standardized methods for evaluating deep learning, machine learning, and hybrid models for the prediction of crop yields. The differences in each of the models that was used within the described studies makes it difficult to directly compare the performance of different models within the existing literature. Thus, the establishment of more standard models for evaluation would help to contribute to the comparability of different studies that aim to investigate the accuracy of these methods.

The additional requirements for many models to effectively be utilized outside of research studies suggests the need for additional development of models that are also scalable, interpretable, and efficient in relation to the data and resources that are available in different environments. While the accuracy of the models based upon the integration of deep and machine learning methods is high, there are still challenges to their scalability. Thus, additional research can be directed towards the development of deep learning and machine learning models that are lightweight and data-efficient, enabling their use in various environments.

Furthermore, because the deep and machine learning models have been examined in relation to their individual methods, future studies should investigate the integration of these models into a unified framework that integrates methods like multi-task learning and ensemble learning approaches into models that use agricultural data sets. Such frameworks can help to address the limitations of existing models while maintaining their scalability and usefulness in agriculture.

VI. CONCLUSION

In general, this research presented an examination of the current literature on machine learning, deep learning, and machine learning models for the prediction of crop yields. Deep learning models have exhibited higher accuracy in relation to machine learning models, and the integration of various methods within deep and machine learning models has exhibited additional accuracy in relation to deep learning models alone.

Results showed that deep learning models are accurate in modeling the complex features of crop yields. However, the reliance upon remotely-sensed data and the development of computationally-intensive models to extract those features limit the scalability and applicability of those models outside of research and resource-constrained environments.

Additionally, there are notable gaps in the literature regarding the development of models that utilize methods like multi-task learning, as well as models that explore the integration of ensemble methods into deep learning models.

These findings indicate the need for future research and development of "next-generation" models for the prediction of crop yields that combine deep learning and ensemble methods within agricultural data sets. Such efforts will enable the gain of accuracy in the predictions of crop yields, while also maintaining their scalability and applicability.

Overall, then, this research suggests both that current approaches to modeling crop yields are lacking in scalability and applicability, yet also that future research will help to fill the gaps in the existing literature and to develop more robust models for agriculture.

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