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A COMPREHENSIVE REVIEW ON CROP YIELD PREDICTION USING MACHINE LEARNING AND DEEP LEARNING APPROACHES

[1]Yash Aditya Mishra, [2]Priya Muskan
[1]Student, [2]Student
[1]Dept. of Computer Science & Engineering, [2]Dept. of Information Technology
[1,2,3]Raj Kumar Goel Institute of Technology, Ghaziabad, India

Abstract : Food security and sustainable agriculture require accurate prediction of crop yield. Machine learning methods, including random forest and support vector machines have increasingly been used in agricultural forecasting [4]. With the increase in remote sensing data and computational power, deep learning methods such as convolutional neural network CNN and long short-term memory networks have shown superior prediction accuracy. Recently, hybrid CNN, LSTM models have been shown to be effective in reconciling spatial and temporal data. However, practical applicability is still hampered by problems like poor data scarcity and the lack of interpretability. This review paper discusses the state of the art of machine learning and deep learning techniques in crop yield prediction. It explores the latest hybrid attention-based architectures, GAN based data augmentation, and explainable AI techniques. The study pinpoints the research gaps and suggests future prospects for developing accurate, transparent, scalable agri-prediction systems.

***IndexTerms*: attention mechanism, CNN; crop yield prediction, Data augmentation, deep learning, Explainable AI, ISTM, Precision agriculture, Machine learning, Remote sensing.**

I.INTRODUCTION

The need for food production increase under uncertain climate leads to high pressure on agricultural systems. Correct forecasting of crop yields would assist farmers, policymakers and agribusiness actors in decision making. Accurate yield prediction can be used for irrigation control, fertilizing strategy decision, insurance distribution and market stabilization. Early of prediction crop yield was based on statistical regression models, which employed the historical yield and weather data. While these models were interpretable, they suffered from a lack of sensitivity to nonlinear relationships. Machine learning methods represented one of major breakthroughs in agricultural prediction research [1]. The addition of random forest, support vector machines and artificial neural networks exhibited improvement to predict complex relationships between soil, weather and crop variables [6], [18]. High resolution satellite and unmanned aerial vehicle imagery became more widely available, completely reshaping the field. The deep learning models could directly handle spatiotemporal data [3], [4]. There are spatial patterns captured through convolutional neural networks on crop imagery, and there are sequential weather patterns learned by long short-term memory (LSTM) network. Hybrid CNN and LSTM architectures are now commonly believed to be the best performing models for multimodal yield prediction [5]. However, even with these advances, lack of data and poor interpretability continue to present significant challenges.

II.LITERATURE REVIEW

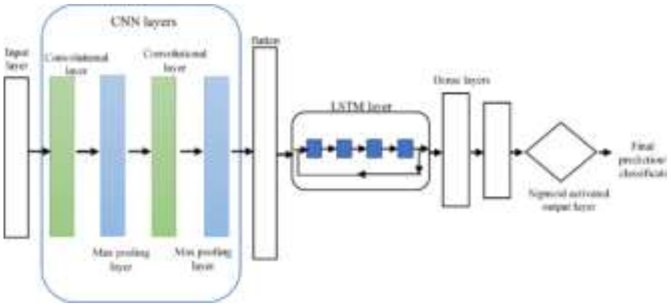
Early works on predicting crop yield were based predominantly on structured agricultural data incorporating rain fall, temperature, soil nutrients and crops attributes [1]. Random forest models gained popularity due to their ensemble framework and possibility of feature importance measure, which can increase interpretability and prevent overfitting [6]. Support vector machines were successfully used to predict the rice and wheat yield, especially on structured data with non-linear trends [18], [19]. ANNs also showed greater modeling capability than classical regression models since they can account for complex soil–crop interactions [14].

Thanks to the high-resolution satellite and unmanned aerial vehicle (UAV) images, researchers have begun applying deep learning methods. Spatial features, such as vegetation indices and canopy density were directly extracted from imagery using convolutional neural networks [9], [13]. These architectures eliminated the necessity of hand-crafted feature engineering and outperformed predictions when applied to image-based yield estimation. Following this, long short-term memory networks were added to the model for sequential meteorological data analysis, which made it possible to model temporal dependencies among different crop growth stages [3]. Combining CNN with LSTM models produced the hybrid models that can deal with both spatial and temporal data at the same time. Hybrid CNN, LSTM architectures were reported could constantly exhibit better performance than that of single CNN or LSTM models in soybean and rice yield prediction [5]. However, despite better performance, several shortcomings were reported in those publications. Deep learning algorithms demand massive labeled databases, which are not readily accessible in many agriculture regions. What is more, the hybrid models normally act as black boxes, producing predictions without satisfactory reasons for their decisions [16]. Such an opaque process does not inspire confidence in users and severely hampers uptake of such applications to real world agricultural contexts. These limitations underline the need to develop interpretable and data efficient frameworks.

III.PROPOSED FRAMEWORK: ATTENTION BASED EXPLAINABLE HYBRID YIELD MODEL

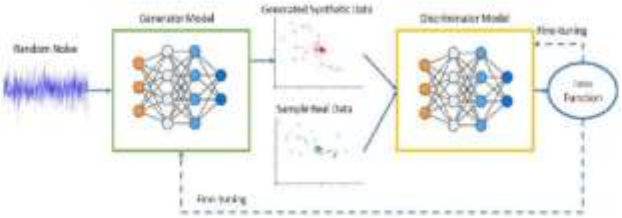
In order to combat these aforementioned limitations, this work proposes an attention based explainable hybrid framework for crop yield forecasting. With the proposed model, spatial images, temporal meteorological data and static soil characteristics are combined with a single architecture. Satellite or UAV imagery are passed through a CNN encoder to obtain spatial representations of crop health and field variability. A stacked ISTM encoder is applied to sequential weather data for the long-term time series. Soil and management parameters are encoded in terms of a multilayer perceptron that contains static context information. An attention mechanism is used to assign adaptive weights on features from distinct data streams. It allows the model to concentrate on important growth periods, or environmental factors. The weighted features are merged together, then they are fed to a fully connected layer for the yield prediction.

Fig. 1. hybrid attention-based CNN and LSTM architecture



To address the lack of data, generative adversarial network for synthetic data generation is proposed. Gan is modeled this way that learn the distribution of images of real crops and generated the realistic synthetic samples. These augmentations help in enlarging the training data and generalizing the model.

Fig. 2. gan-based data augmentation workflow



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Explainable AI methods like SHAP are utilized for enhanced interpretability [16]. The mathematical value of each input feature to the predicted value is characterized by SHAP values. Distinct instances are adequate rainfall during blossoming, which might decrease anticipated yield, and high levels of nitrogen making it higher. These descriptions humans the transparency and trust of users.

IV.RESULTS AND DISCUSSION

Quantitative performance of the hybrid framework is assessed using classical regression measures. We use the root mean square error as the main performance metric as it indicates prediction deviation in total [1]. Performance is also evaluated by mean absolute error and coefficient of determination. Ten-fold cross validation makes the model robust and decrease the bias because of random data splitting. The model is then compared with conventional machine learning models like random forest and normal deep learning models, CNN and LSTM. Hybrid attention-based model should give better performance by having optimized feature fusion and representation learning capabilities.

Table i: comparison of prediction approaches

Problem Area	Issue in Traditional Systems	Proposed Solution in Paper
Data Scarcity (Limited Data Availability)	Insufficient, incomplete, or noisy datasets reduce model accuracy and generalization capability.	Synthetic crop images are generated to increase dataset size and variability.
Poor Model Interpretability	Deep learning models behave like black boxes, making it difficult to understand prediction results.	Feature contribution is explained to show how each variable affects crop yield.
Inefficient Use of Multi-Modal Data	Models focus on only one type of data such as spatial or temporal, limiting performance.	Multiple data sources are combined into a single framework.

V.Conclusion and future work

Predicting crop yields: From statistics to multi modal deep learning Crop yield prediction research has evolved from traditional statistical regression to sophisticated, multi-modality deep learning frameworks. Machine learning techniques enhanced the capacity for nonlinear modelling and deep learning realized automatic spatial and temporal features extraction. Hybrid CNN LSTMs are indeed highly predictive, but related challenges

i) concerning data availability and

ii) to model interpretability prevail. Gan based augmentation increase dataset diversity, and explainable ai methods improve transparency. Light weighted and edge deployable architectures that integrate an economic forecasting with a yield prediction system will be considered in future works. These advances will enable scalable, precise and credible agricultural decision support systems.

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