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Soybean Crop Growth and Yield Prediction using Deep Learning Model

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ABSTRACT
Agriculture is a fundamental pillar of food security and economic development, with soybean recognized globally for its high nutritional value and versatile applications in both food and non-food industries. Accurate soybean yield forecasting is critical for addressing key agricultural challenges, including efficient resource utilization, sustainable production, and climate change adaptation. Recent advancements in deep learning and remote sensing technologies, incorporating multi-source data such as UAV imagery, satellite data, and field measurements, have significantly enhanced yield prediction accuracy. This research proposes advanced deep learning models, utilizing spatial-temporal frameworks like CNN and LSTM, for precise, fast, and non-intrusive soybean yield assessment. Challenges such as dataset availability, computational demands, and regional variability in soil and climate are addressed to improve model flexibility and scalability. Furthermore, integrating hyperspectral, thermal, and RGB imagery enhances stress detection. This study contributes towards developing scalable, decision-support tools for sustainable and precision agriculture.

Keywords: Soybean, Crop Growth, Yield Prediction, Deep Learning

INTRODUCTION
This is a substantial sector since it plays a major role of contributing towards the delivery of food security besides contributing to economic stability in the several parts of the globe. Qualitative: Between different crops the most valuable crop because of nutritional importance and multiple use in foods, feeds and others (Liakos, 2018) and (Gill, 2021). The overall outlook of growth and yield for soybean crop is fundamental to influence the challenges faced with regards to resource deployment, proper utilization and food security (Wilkerson, 1983). Yield estimate itself is one of the highest problems yields representing, crop market design, crop protection and harvest working are all closely related to it. Soybean is not only unique of five leading crops in the world then also the extraordinary protein grain and oil crops (Zhang, 2022). Soybean pods are a homologous leaf (Lu, 2022) that achieves this function for grain yield. Then, it is essential to estimate the value of soybean plants in the pod at progress and growth stages also the phenotypic types of the pod variations. But it is similarly one of the firm processes of credentials showing soybean variations (Zhao, 2021).

Well, the grain rule creating and food security specifically in areas facing high population density and or things of weather change may help from the technology Prediction at field or farm level and mapping of within field yield variability for best use of fertilizers, water and pesticides for crop management is crucial (Pantazi, 2016) and (Wang, 2014).Yield prediction by using early-season data can help in enhancing the production of crops and the resulting profit while at the same time minimizing input utilization and negative impact on the environment. Soybean is a multipurpose pulse, which can be collected into different modules depending on their properties and applications (Javed, 2023). Some of the several types are yellow soybeans which are frequently used for making oil and soy protein food products and the black soybeans which are known to comprise antioxidants. Some soybeans are fresh green in color which are consumed as snacks and other small variety used in products like tofu and soymilk etc. These types determine versatility and standing of this crop in the farming structures across the world (Egli, 1991).

Fig. 1. Soybean Crop Growth

Despite it being possible to estimate yield with the help of several methods, existing model only produces an interval estimation of yield for one kind of crop only. In other words, there is no model utilizing remote sensing data targeted at yield prediction of several crops simultaneously. On one operational level the scholarly question which this paper enquires can be described more specifically as: to determine what kind of knowledge regarding the yield prediction of one crop can be extrapolated to yield prediction of the other crop. Since individual models are required for each kind of crop and often for each field, long algorithm processing times imply that, in general, machine learning cannot be successfully applied to large zones (Jin, 2018) and (Sindiramutty, 2024). It said crop growth and yield models are derived from soils, crops, and climate factors as being central gears. Water availability is regularly among the foremost factors utilized in analysis of yield within the farming (Sadras, 2001). validated that soybean yield and corn yield variation are explained by water stress. What was more apparent is that causes of variability within a given region could be attributed almost entirely on effects due to rainfall. That temperature had no impact on yields.

These recent crop growth and yield prediction deep learning models have been effective in applying data processing methods and multisource remote sensing technologies. These models analyzed multi-dimensional data that is collected with UAVs, satellites or ground sensors, and provide precise and sign scale estimation of yield. Compared to the conventional methods where the prediction is based on the linear statistical models, the deep learning methods can find other, nonlinear dependence between stages of crops, changing environmental factors and practices in farming that are needed when the agriculture is constantly progressing. Improved yield prediction relies on the accessibility of remote sensing records for incorporation into a system subsequently. When hyper-spectral and thermal are integrated into RGB, the possible application fields of remote sensing are crop inspection for health, biomass estimation, and identification of the effects of stress factors, such as water or temperature stress. These data types made the environment more enriched with spatial data so important for prediction of yield of soybean at field as well as regional level. The flexibility of carrying out the monitoring in this manner also allows one to identify early growth stages and assess constraints to yield potential at a time when the constraints may yet be responsive to management manipulation. Consequently, yield prediction in early season is useful in several ways concerning precision agriculture study. Yield estimation when early enables farmers to make necessary decisions such as; usage of fertilizers and attend irrigation and pest control during early periods in growth (Sindiramutty, 2024). This does a lot of good in helping with better utilization of the inputs used but also in helping them to go green and not to use a lot of chemicals in production. Also, reliable early season forecasting allows us to define high productivity genotypes, especially for breeding programs aimed at increasing crops productivity with higher yield potential (Gaur, 2021). However, there are still some issues that prevent deep learning models for yield prediction to be widely used: In view of this, the following is a list of key challenges:

The first main problem revolves on the availability of labeled data, an essential factor in training deep learning networks. These models remain an experiment due to high computational necessities and the need for large datasets particularly in a situation where the farmers and researchers implementing them have limited access to technological resources. Variation in soil characteristics, climate conditions, and management practices further confounds the issue of cross-geographical model portability (Hossain, 2020) and (Shah, 2024). Consequently, the accuracy of the models generating valuable predictions in one region is not precisely reflective of the models' ability to do so in another Furthermore, traditional models used to forecast the crop yield is achieved on a particular crop without any methods of transfer learning on another different crop. Current research on generalized models that can predict the yield of one or more crops such as soybean, corn and wheat at the same time is ongoing. These kinds of models would be particularly useful for large-scale farming enterprises and could greatly improve the computational efficiency of the models for their development and deployment. These skills, which are portable from one set of ecosystems to another, are the only way to continue progressing in the field of precision agriculture and making progress toward increased food security around the world.

PURPOSE OF STUDY

This study is therefore to apply deep learning methodologies to determine their usefulness in estimating growth or yield of soybean crops. As the use of aerial imagery in precision agriculture continues to grow, there is an even greater need for accurate grain yield prediction to maximize the returns on resource investment. Deep learning to review several factors, including climatic information, soil type, variety, and growth of soybeans. Forecasting their on growth and yield types it easier for increase in farming creation, minimizing losses and management of properties. As a result, this study aims to improve prediction accuracy using remote sensing data and UAV imagery. Conventional prediction methods involve shortest assessment or the simplest linear structures, which may sometimes take a lot of time and are extremely incorrect and do not consider environmental interfaces. In the long run, the development of a decision support tool is realized to help farmers in decision making potentially enhancing crop management and production. It is only hoped that improved predictive models resulting from this work will help to underpin more sustainable cropping systems in the long run.

MOTIVATION

Deep learning for soybean crop growth and yield rate is attributed to the rise in the global consumption of soybeans as one of the most important agricultural products. Soybean output forecasting in a tropical environment is essential to make appropriate management decisions, feed the population, and obtain high yields. In traditional yield forecasting, yield is estimated from available observations and can be a time- consuming and subjective process. Due to the progress for deep learning, the increased utilization of large-scale remote sensing data and the development of complex neural network structures can lead to improved prediction accuracy. UAV- based imagery and satellite data have the potential of offering real-time and accurate deep learning models that would assist farmers in decision making (Muzafar, 2020) . Besides, it can assist in decisions made for resource utilization, pest and disease control as well as market planning based on accurate yield estimations. In decision, the resolution of this study is to help the agricultural sector to achieve long term and sustainable development using AI in managing crops.

EXISTING APPROACH

Most of the works converse the uses of advance deep learning in forecasting crop produce and several authors have contrasted it with basic and basic machine learning and evaluated the structures that influence them but none of these do not discuss the features and boundaries of several types of deep learning(Gill, 2022) and (Lee, 2020). It is important to understand what kind of model suits best to predict, which type of crop and what potential the model is as well. It suggests that the variety of the appropriate deep learning system can be largely predicated on the precision of the last estimate (Zaheer, 2023). This paper is to give an organized as well as straightforward overview of deep learning for harvest yield valuation in addition to providing a more elaborate account of different categories of deep learning for crop yield valuation, benefits and drawbacks of using deep learning forms of yield estimation, and some of the key crops that can be well analyzed using deep learning models (Alwakid, 2019). Benefits of relating deep learning for cropping yield estimate discussed and several factors working towards cropping yield estimation and will contribute towards enhancing the knowledge base and research perspective for the future work related to cropping yield estimation. A Convolutional neural network is a kind of deep neural network that has been exclusively built for the structures such as pictures. RNN is a kind of neural network which was invented with aim to solve the issue of processing sequential data because it has something that resembles memory – internal states. A BNN is a neural network that makes predictions about the variance based on Bayesian probability.

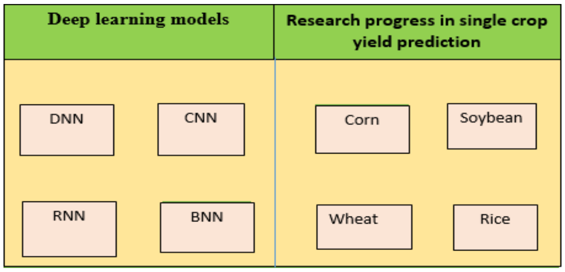

Fig. 2. Subheadings in the Article Presidency of. DNN is ANN, that is also known as Deep Neural Network.

DEEP LEARNING TECHNOLOGY

It is difficult to construct flexible harvest yield prediction simulations using the conventional process such as the static regression model as well as the mechanistic model due to limits and uncertainties. A little few of them have used machine learning methods such as regression tree, random forest, and artificial neural network for crop produce estimation (Basso, 2013) The output, that is the crop yield, is a function of several inputs which include weather conditions and soil conditions which could be very difficult for the machine learning models to determine(Humayun, 2023). Also, the constraint of supervised learning methods presents in machine learning approach which makes it difficult to get the non-linear relationship of input and output (Islam, 2021). However, with recent technological advancement, it can be argued that it is feasible to design a new crop yield estimate model through deep learning. The capability to interconnect with other layers within the pyramid structures also, the deep learning can handle with the unstructured and the unlabeled data sets, which set it apart from the other traditional machine learning techniques . In general, it is used extensively in the farming field because it can examine the data, learn the association between factors, and build models. These methods can perform feature extraction for the massive data sets in the unsupervised context. According to the literature, deep learning approaches are more efficient than the typical machine learning methodologies in feature extraction.

A precise harvest yield estimate is based on the aspects that are leading in growth of the crop and deep learning has a good extraction ability from the given dataset. The deep neural networks have several layers which change the arbitrary contribution data into removed form at all layers . It requires several unseen layers or layers with different dimensions to provide a relationship between input and response variables that cannot be defined as a linear sequence . However, they are firm to sequence and require established hardware and enhancing methods (LeCun, 2015). Thus returns the statement that increasing the number of unseen layers is actual but not limited, which can be fixed by firm methods. Some of the problems such as gradient vanishing in deeper neural networks can be mitigated by employing remaining skip associates for the system (Khaki, 2020) and (Szegedy, 2015). Hence, specifics of the method are listed below:

1) Artificial Neural Network : They are simply systems that have been developed based on the structure of a single neuron of the social mind. There are the nodes that are associated with one to another, and the neurons are assembled into layers. It has three layers: an input layer, an unseen layer, and an out layer as its fields of one another. The input units are the first layer of neurons and are given as input layer while the second set of neurons that are interconnected perform the function of the network and this is the unseen layer and the final layer which is the output layer produces the result. Besides, the weights assigned to it in the first iteration are random to initiate the learning procedure.

2) Deep Neural Networks : A DNN can be described as related to anticipating neural networks with numerous unseen layers and are fully associated. While for the hidden layers, the activation function used is ReLU and for the loss functions, there is the L2 standardization and mean squared error.

3) Convolution Neural Network : CNNs also have semantics which makes seeking important features within data samples easier than in normal use of neural networks. Convolution layer is the convolution and stimulation purpose that was performed on the layer, and it is well used in feature removal . Now convolution operation involves a Filter and a feature map. In other words, where the filter weights are maintained across the input layer, what we get for this specific filter is a feature map. Moreover, in this work, the pooling operation that is used helped in this work also down-sample because feature detection can be boosted (Yamashita, 2018). They are then accepted to the nonlinear activation role because the activation role employed in the output layer he introduced nonlinearity into it. While FC layers are placed after the convolution layers; if the FC layers are included the network can learn the relationship of the feature to the target (Nevavuori, 2019).

4) Recurrent Neural Network : One of the most common models that are used in time-series data modeling is Recurrent Neural Networks (RNNs), which are good at taking temporal dependencies. Specifically for growth and yield prediction of soybean crops, RNNs are suitable as the model can take in sequential inputs, such as weather data, phenological stages, and previous yields (Khaki, 2019). RNNs can retain information from previous time steps and therefore can model crop growth over the period of a growing season. Other related works have focused on the custom of RNNs in

soybean yield estimate regarding environmental factors such as rainfall, high temperature, and soil condition. However, RNNs have been applied in the analysis of multi-temporal satellite imagery and field data captured by UAVs where remote sensing biomarkers have been shown to be related to yield performance indicators. However, the problem of traditional RNNs is the issue of disappearing and explosion gradients that results in the reduced ability to model long-term dependencies, which has given rise to more advanced forms of RNNs such as LSTMs and GRUs (Park, 2023). Such higher order architectures have proven to offer higher accuracy in predicting the nonlinear transformation functions relating the input variables to the soybean yield predictions, which makes RNNs useful tools in precision agriculture

5) Binary Neural Network : BNN uses the neural net- work and then work with probabilities as weights inside the networks. Overfitting problems are avoided with the aid of Bayesian neural networks while models presented do not require large amounts of validation data for checking regularization parameters. When training BNN on large datasets, the level of accuracy can be enhanced. In other words, BNN can be described as standardized by adding epistemic improbability in the loads of the neural networks [30]. This can be thought-of as an ensemble of forecasts for an infinite number of neural networks where the burdens have been drawn from a specific probability. As it has been earlier discussed in the paper, Bayesian Neural Networks combine factors of neural networks and Bayesian approaches. They are better able to model and make inferences based on uncertainty inherent to data. However, they excel in minor section learning by managing previous information and assistance in model simplification properly. This makes best guess and reduces overtraining while improving the prospects of the recognition model generalization. Therefore, while the relative advantages of employing BNN model are apparent especially concerning sample size in the agricultural application, it is also important to appreciate the following shortcomings. In Bayesian methods, commonly the sampling of the posterior distribution of parameters is performed and this results in high computation and often worsens when the models scales are large or if the data size is vast. In high computational complexity especially when applied in real time applications such as agricultural yield prediction, the prediction speed could be slow or may not even meet the real-time requirement. One often must tune the prior distributions and the sampling methods involved in building BNNs in the first place. Hyperparameters' tuning can somehow improve the structure of models and in most cases, it presupposes some prior knowledge. Create table1 which compares the various types of neural network models including DNN, CNN, RNN, BNN where the ability to predict or analyze the performance of crops such corn, wheat, rice, and soybean is involved.

The performance of different deep learning methods and the task of crop analysis are presented in this table. Most of the research papers use employment optimized algorithm for a given prediction task. CNN is implemented to identify corn diseases while DNN and RNN are implemented to predict wheat and rice yield, respectively. BNNs are applied for estimating environmental stress in soybeans and wheat yield prediction depending on weather conditions. By looking at the presented table, one realizes that deep learning methodologies are quite efficient in predicting and improving the crops qualities.

TABLE I COMPARISON OF YIELD PREDICTION TECHNIQUES

Reference No.	Paper Name	Method	Performance
Khaki, 2020	Corn and soy-b e a n crop yield prediction	CNN, RNN	RMSE for Corn yield:24.10 and Soybean yield:6.35
Bhojani, 2020	What crop yield prediction	ANN	MAE, MSE, RAE, RMSE, MAPE and PRSE
Wang, 2020	Wheat crop yield prediction	DNN	R-squared:0.77, RMSE:721 kg/ha, MAPE: 15.38%
Guo, 2021	Rice crop prediction yield	BPNN, SVM, RF	RMSE (R-squared): BP:800 (0.24) kg/ha, SVM:737 (0.33) kg/ha, RF: 744 (0.31) kg/ha
Sun, 2019	Soybean crop yield prediction	CNN, LSTM	RMSE:329.53, R-squared:0.78
Guo, 2014	Wheat crop yield prediction	ANN(MLP)	MSE:0.0001
Terliksiz, 2019	Soybean prediction yield	CNN	RMSE:0.81
Kros, 2020	Soybean, crop prediction corn yield	ANN	for corn RMSE is smaller related to soybean

COMPARATIVE ANALYSIS

These include CNNs, RNNs, DNNs, and BNNs which are used in the prediction of harvest yields. DNN models are mainly appropriate for huge data because the model can per- form feature of higher order. CNN models have proved to be very effective in some applications RNN models are incredibly useful when it comes to identifying nonlinear patterns in the data in general and over time especially. The earlier spreading of BNN models can be selected according to prior information as well as the distribution of data which helps in guiding the overall training process. Therefore, regarding the choice of the model, it is necessary to make a choice depending on the given problem and the characteristics of the data, as well as considering logistic aspects. The DNN model has more than one hidden layer, hence, has a better understanding of the features of the data it has to work with and has a better way of modeling non-linear data. Consequently, DNNs perform better when dealing with results and when the features used are in some way dependent on one another. They serve well as a means of solving problems in agricultural yield prediction where the interaction between different factors is employed. Like other types of neural net- work models, DNNs have even more capabilities of modeling the characteristics of the data than basic ANNs. However, they are very slow and require large amounts of training data and are very sensitive to overoptimized. CNN can accept image and structural data, can grab local features in turn and has higher satisfaction of agricultural data with the spatial character such as soil feature distributing regionally. It can be trained on big data set in a specific domain and then fine- tuned on a small data set of another domain that makes it possible to transfer knowledge from one domain into another. It can be helpful should you need to boost the model's precision when there are not many samples. In farming yield estimate the material such as value of the soil and which harvest is sowed where is very crucial. The CNNs are known to perform well when extracting spatial characteristics in such scenarios. For instance, CNNs could present certain limitations especially for non-spatial data as compared with fully connected networks. Secondly, CNN models rely on a vast array of labeled data to work with, and bad data collection can significantly influence the operation of the model. These RNNs are appropriate for analyzing sequential data such as climatic data and data on crops' progress. They can incarcerate the rates of change in growth of crops in the long-run and the short run hence incorporating time among the variables. But they excel in harnessing long-term memory and periodic characteristics, but they are poor in learning a non-linear mapping and They are poor in predicting non-periodic occasionality. The problem of long-term dependencies is resolved by LSTM one of RNNs' variants, as the appearance of gate structures allows restraining the information flow and enhances the mechanism of capturing long-term memory information (Tian, 2021). Thus, it demonstrates considerable memory efficiency, allowing information storage and transfer over long distances. In case of long sequences, it is found to be superior in performance related to other traditional models. RNNs are good in handling temporal data whereas CNNs have a improved performance in spatial data. Several proposed that integrating two types of networks like CNN-RNN can give better performance as well as in crop yield prediction as this utilize combined network architecture of CNNs and RNNs. However, when it comes to sure data has temporal features and spatial material such as video data RNN or CNN may not be optimal in extracting the structural features of data and other models or methods are required for processing. Compared to other forecasting techniques BNN has advantages of giving probabilities of uncertainties in predictions, which is important in crop yields, since crop yield predictions depend on influential factors like climate, earth, pests and diseases the suspicions associated to these improve the accuracy of the forecast. However, there are limitations in BNNs used in the modelling of uncertainty and parameter sharing that need to be addressed to enhance their applicability in scarce resource allocation, sustainable agriculture and so on. The proposals to integrate both CNNs and LSTMs with multi-source remote sensing data to predict crop growth and yield represent revolutionary architecture to support agriculture. With UAV imagery, climatic variables, and soil data, these techniques improve forecast precision, allow yield prediction during the early growing season, and prevent waste of resources.

CONCLUSION

Accurate soybeans yield predictions in tackling global challenges such as food security, resource optimization, and sustainable agricultural practices. By leveraging advancements in deep learning innovative methods for crop yield estimate have been developed that are scalable, non-destructive, and environmentally friendly. Models such as CNN and LSTM have demonstrated their potential in analyzing spatial and temporal data, enabling precise and early-season yield estimations. The integration of multi-source data, including UAV imagery, satellite inputs, and field observations, enhances the prediction accuracy and provides esteemed insights into reasons influencing soybean progress, such as soil quality, climatic situations, and phenotypic traits. Early predictions empower farmers to make informed decisions on fertilization, irrigation, pest management, and breeding strategies, ensuring better resource efficiency and reduced environmental impact. However, challenges such as high computational requirements, regional variability, and the need for extensive labeled datasets persist. Addressing these challenges through transfer learning and generalized models will enhance the portability and scalability of prediction frameworks across diverse regions and crop types. The findings of this research pave the way for the development of AI-driven decision support systems that not only improve yield predictions but also contribute to sustainable agricultural practices. By fostering precision agriculture, this approach supports global food security initiatives, minimizes environmental degradation, and ensures long-term agricultural productivity. Future work should focus on refining these models, integrating additional data sources, and expanding their applicability to diverse agricultural ecosystems, thereby driving innovation and sustainability in modern agriculture.

FUTURE WORK

More improved future work regarding soybean crop progress and crop yield estimate using deep learning might be the concern of multi-source data involving of UAV imagery, satellite imagery and climate data. Thus, demands for more elaborate and flexible models which will be able to forecast environmental situations as well as different types of crops can be recommended. It can also include extreme real-time monitoring and forecasting structures connected to IoT for farming use. Moreover, considering more difficult approaches such as transfer learning and XAI can enhance model performance and readability. Finally, large scale field practical validation and working related to agronomists would keep the applicability and adoption intact around farming.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

ETHICAL INFORMATION

This research did not involve any human participants or animals. Ethical guidelines have been followed as per the policies of the respective institutions.

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AUTHOR CONTRIBUTION

Ayesha Munir conceived the core idea and led the writing of the manuscript. Sidra Tahir contributed to the literature review and prepared the initial draft of the paper. Ghadah Naif Alwakid provided valuable input on the methodology and supervised the theoretical framework. Rafeef Taresh Suliman Alshammari contributed to structuring the paper and verifying technical accuracy. Saira Muzaffar critically reviewed, edited, and refined the final version of the manuscript.

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