A SYSTEMATIC REVIEW ON DEEP LEARNING APPLICATIONS FOR CROP YIELD ESTIMATION USING REMOTE SENSING DATA

2201CE61—SUDHANSHU KUMAR

2201CE62—SUMIT SUHAN

2201CE63—SRIJA SUNKARA

2201CE64—TUSHAR KUMAR

2201CE68—ARUN NAG

2201CE69—ROHIT KUMAWAT

2101CE06—ANAND KUMAR

ABSTRACT:

In the realm of modern agriculture, challenges from climate change, resource limitations, and the recent global pandemic loom large. Tackling these adversities necessitates scientific and technological breakthroughs to meet the escalating demand for food worldwide. Notably, recent progress in remote sensing and Artificial Intelligence (AI) presents a unique opportunity to accurately evaluate and manage crop conditions on a broader scale, propelling predictive and prescriptive agricultural management tools. Deep learning has become an important Crop Forecast Tool, allowing models to remove features and learn from the dataset. This qualitative literature review provides an in-depth analysis of existing research in specific areas to guide our analysis of results and crop patterns. The research targets on leveraging the benefits of learning in crop forecasting, developing effective electronic tools for data collection, and various factors that influence forecasting results. By this study we found that long-term memory and convolutional neural network are the ultimate advanced methods in crop forecasting. One of applications of electronic equipment in remote sensing is satellite remote sensing technology, specifically Module Intensity Spectrometry (MODIS). By utilizing deep learning methodologies like CNNs, the authors aim to establish an effective model for crop yield prediction using both Normalized Difference Vegetation Index (NDVI) and RGB data acquired through UAVs. The paper also investigates the impact of various CNN parameters, training algorithms, and regularization strategies on prediction accuracy. This research contributes significantly to the field of precision agriculture by demonstrating the potential of deep learning and UAV-acquired data in enhancing crop yield prediction, with implications for future smart farming practices.

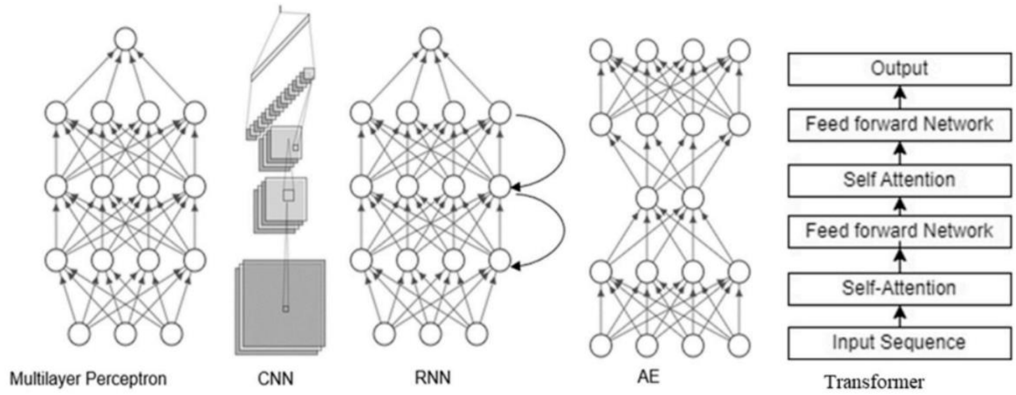


Figure 1. Different DL models: All the models have an input layer, output layer and hidden layers for encoding and decoding. Hidden layers learn representation and perform mapping based on learned features.

INTRODUCTION:

This article provides an overview of remote sensing technologies and food maps and focuses on their recent applications in crop forecasting from 2018 to 2023. Advanced technologies such as diversification of fertilizers using machines like Green Seeker and Crop Circle were found a place in the agricultural sector. Agriculture is the main source of economic growth in many countries and meets basic food and fibre needs. Over the past years, technological advances like Green Revolution were revolutionized agriculture. Yield forecasting is becoming increasingly important as food security issues increase. Hunger is the biggest problems in the world, and increasing production of crop is one of the solutions to solve this problem. Deep learning has become an important technology widely used in agriculture thanks to its rich data and high-performance computers. Studying this relationship requires complex data and effective algorithms from deep learning. Accurate
forecasts of crop manufacturing facilitate critical targets as figuring out the top-of-the-line profile of vegetation to crop, allocating authorities sources, effective planning and

instruction of aid spread, and choice regarding imports and exports in more commerzliazed structures. Preliminary the researchers work shows promising results in predicting soybean

Crop Yields in Argentina using deep learning techniques and a transfer learning approach to predict Brazil soybean harvests with a smaller amount of data. They choose Brazil & Argentina soybean harvests as their commercial importance are relatable. In the vast fields of agriculture, where climate change, dwindling irrigation water, and a dwindling farm workforce cast ominous shadows, a new challenge emerges - the silent but powerful COVID-19 pandemic, threatening food production across the globe. To confront these formidable foes, agriculture must embrace innovation. Enter dynamic crop simulations and the enigmatic realm of Artificial Intelligence (AI). But it is the advent of Unmanned Aircraft Systems (UAS) that steals the spotlight, offering the promise of harnessing colossal data streams. With UAS in hand, a new horizon opens for managing agricultural systems with finesse and improving their resiliency and efficiency. Yet, as we tread these uncharted skies, obstacles persist in the widespread adoption of UAS technologies. The future whispers of a harmonious blend of UAS and spaceborne remote sensing, promising a panoramic view of sustainable agriculture on a national and global scale.

Accurate crop forecasting and planting is critical to food security and agricultural decision making. Remote sensing data, combined with deep learning, is a powerful tool for these tasks. Deep learning models like CNN, RNN, and AEs are commonly used. TensorFlow and Keras are popular frameworks for implementing these models. The data sources are mainly satellites and UAVs, often integrated with environmental data. The focus is on various crops, with corn and soybeans frequently studied for yield prediction. These techniques help ensure a stable food supply and informed agricultural management.

Future research in crop production and forecasting faces some significant challenges and opportunities driven by the combination of deep learning and remote sensing. These issues and directions for future work are summarized below:

1. **Data Availability and Diversity**: One of the primary challenges in yield prediction and mapping of crop is the limited availability of target data for various crops across different regions and timeframes. Deep learning models require substantial training data, and the scarcity of such data can hinder model development. Future research should focus on addressing data scarcity by exploring techniques such as transfer learning, unsupervised learning, and data augmentation. Efforts to create benchmark datasets that encompass diverse spatial and temporal characteristics can also aid in standardizing model evaluation and comparison.

2. Alternative Data Sources: To overcome data scarcity, researchers should consider alternative data sources. Crowdsourcing, social media images, and interviews with farmers who are working on crop can provide valuable training data. Additionally, closed-range oblique images from platforms like Google Street View can be explored to augment training datasets. These alternative sources can contribute to collecting data for specific regions and crops where traditional data may be lacking.

3. Standardized Benchmark Datasets: Creating standardized benchmark datasets is essential to facilitate fair and consistent evaluations of proposed deep learning models. These datasets should cover various time periods, locations, spatial resolutions, and sensor types to ensure that models can perform reliably under diverse conditions. Access to these standard datasets can encourage collaboration and enable the development of global models.

4. Domain Adaptation and Weakly Supervised Learning: Techniques like domain adaptation and weakly supervised learning show promise for addressing the scarcity of target data. Domain adaptation allows models to transfer knowledge from one domain to another, even when data distribution varies. Weakly supervised learning leverages limited or noisy labels to train models effectively. Further research and validation of these techniques are needed, especially in scenarios with multi-temporal data and varying environmental conditions.

5. Curriculum Learning and Few-shot Learning: Curriculum learning and few-shot learning methods can enhance existing crop mapping and yield prediction models. Curriculum learning involves gradually increasing the complexity of training data, enabling models to learn progressively. Few-shot learning focuses on training models with very limited labelled examples, a valuable approach in cases where detailed target data is sparse.

6. Unsupervised learning: Unsupervised studying strategies can locate hidden patterns and styles in records without relying on pre-written data. This is particularly useful for investigating the suitability of unnamed rich fields in remote areas for crop and yield estimation.

7. Predictive Uncertainty Modeling: Combining deep learning models with Bayesian statistics offers a way to model predictive uncertainty. This is crucial when dealing with limited training data, as it helps provide a measure of confidence in predictions. Developing methods that effectively incorporate uncertainty estimation into crop mapping and yield prediction models can enhance decision-making processes.

Building the Convolutional Neural Network (CNN): The authors designed a CNN for predicting crop yields, leveraging the extracted image data. The CNN architecture generally followed the structure proposed by Krizhevsky et al., with convolutional layers having 64 kernels and two fully connected layers with 1024 neurons each.

Optimization and Hyperparameter Tuning: The study went through an iterative process to optimize the network. This involved evaluating the performance of different training algorithms, assessing the impact of the depth of the network, and fine-tuning hyperparameters like learning rates and weight decay coefficients. Sensitivity to initial parameter values and the effect of regularization techniques, such as L2 regularization and early stopping, were also examined.

Overview of the Existing Approaches:

1. To calculate the output (crop yield), the machine learning model works on different inputs (such as air composition and the soil) that can be very complicative. Additionally, machine learning ways cannot capture the relationship between input and output.
2. Compared with traditional machine learning methods, deep learning methods are more effective in extracting objects. Since crop yields are predicted based on the impact on crop growth, deep learning can extract features from data available.
3. Moreover, the overall performance of deep gaining knowledge of may be improved the usage of various techniques consisting of stochastic gradient descent, batch normalization, and efficiency.
4. Artificial neural network is a simple neural network that follows the neural structure of the human brain.
5. DNN is a type of feedforward neural network with multiple connections, all in hidden layers.
6. BNN uses Bayesian neural networks. Convolutional layers have convolution operations and activation functions that perform feature extraction. Convolution operations include filters and custom maps.
7. Using the convolution process (FC) after the convolution process; the network can learn the plan by adding the FC layer.
8. Long-term memory is a type of recurrent neural network which can be learn data over period using gradient-based algorithms.

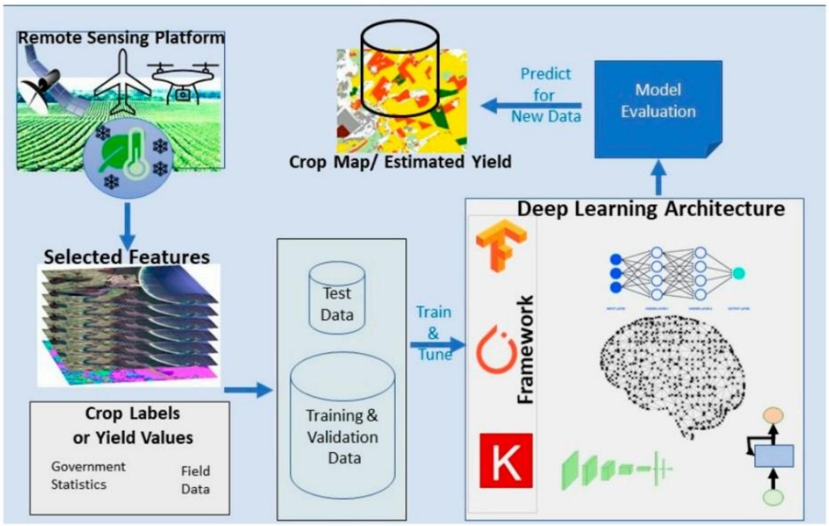


Figure 9. Typical approach for RS- and DL-based crop mapping or/and yield-estimation studies.

Breakthroughs in Remote Sensing and AI:

Remote Sensing Technology Advancements: Highlight how remote sensing technology has evolved, including satellite imaging, unmanned aerial systems (UAS), and the increasing availability of high-resolution data. Artificial Intelligence in Agriculture: Elaborate on the applications of AI in agriculture, such as crop monitoring, disease detection, yield prediction, and automated decision support systems.

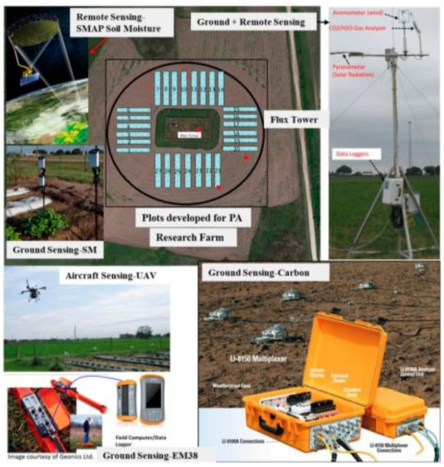
Challenges in Modern Agricultural Practices:

Impact of Climate Change on Crop Production: Discuss the specific effects of climate change on agriculture, including altered weather patterns, increased pests and diseases, and shifting growing seasons. Resource-Scarcity: Water, Land, and Labor: Detail the challenges related to dwindling water resources for irrigation, land availability, and a decreasing farm labor force, which are putting pressure on food production.

IMPORTANCE OF REMOTE SENSING:

Remote sensing based on information and communications technology often produces a lot of spectral data because crop forecasting uses spatial, spectral, radiometric and technical data that are in high demand. In recent years, the introduction of satellite remote sensing technology has greatly increased the efficiency and effectiveness of land use and cover mapping at regional, national and international levels.

Distance measurements are collected several times during the growing season to measure various parameters related to crop water needs, including soil moisture and crop yield. These indicators help predict the water level of crops and plan irrigation accordingly. Remote sensing technology is also widely used in vegetation mapping in agricultural fields to implement specific weed control strategies. Plants can be distinguished from crops based on their unique spectral signatures, which relate to their growth stages and physical characteristics that differ from parent crops.

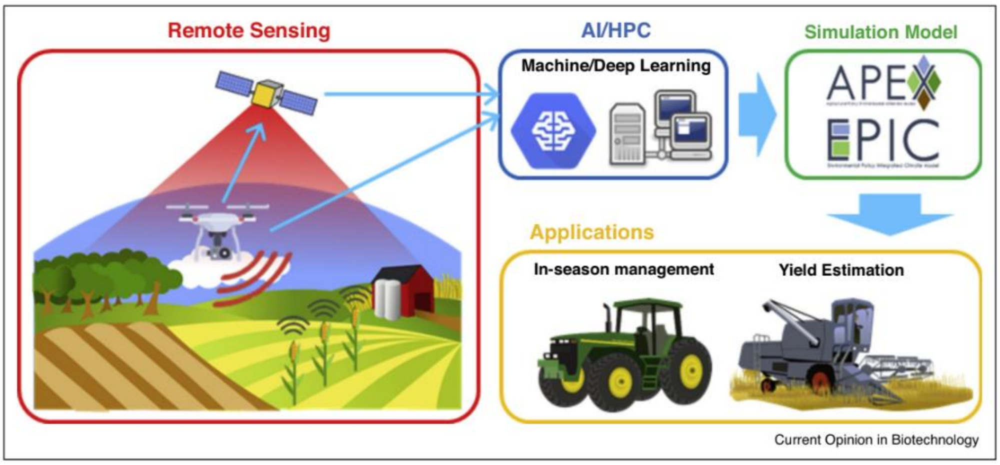


Using remote sensing data this research discusses about use of deep transfer learning in the topic of predicting crop yields. Specially in farming where correct yield predicting is seems difficult for decision making, the researchers find out the probability & productiveness of deep knowledge learning models to upgrade crop yield prognosis purity. In this research paper by using remote sensing data, purpose of the researchers is to adopt deep learning models to the work. Also using data from sources like satellites researchers are examine a path to use modern computer technologies to predict production of crops.

The remote sensing has the potential to contribute to crop yield estimation at various stages of the agricultural process, from land preparation to harvesting. However, no matter several research on the subject, there may be a brilliant loss of established strategies and frameworks that are both accurate and reproducible and may be implemented throughout various climatic, soil, crop, and management conditions.

Remote Sensing for Data Acquisition:

Tracking of environmental elements, other framework, and crop growth may be completed the use of numerous units and methodologies, such as floor commentary, far off sensing, worldwide positioning structures, and on-field surveying. Remote sensing technology is the acquisition and analysis of information about the world and its objects by an instrument placed in the atmosphere or a satellite, without any physical contact. It is the process of tracking and recognizing places on Earth by measuring emitted and reflected radiation using sensors. Combinations of spectral measurements distinctive wavelengths are referred to as spectral indices



Advances in digital agriculture will benefit from the integration of remotely sensed data, advanced crop simulation models, and artificial intelligence (AI). In-season prescriptive tools and yield forecast capabilities will facilitate crop management and marketing projections.

Impact of Vegetation Indices and environmental results:

The menu is designed to increase sensitivity to the characteristics of plants while reducing characteristics such as soil background and orientation or weather. Due to the relationship between display indices and biophysical parameters, they are widely used to determine the nutritional level of plants, mostly in relation to nitrogen, for vegetation and relative to classify flora and to agenda crop control.

In the pursuit of crop yield prognosis using remotely sensed facts, researchers made use of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery. This resource offers wide-ranging and easily accessible coverage of the entire globe. However, since the MODIS cropland mask doesn't differentiate soybeans from other plantation, researchers opted to exclude regions contributing to the bottom 5% of total manufacturing in Argentina and Brazil. This strategic decision aimed to focus the training of their models solely on locality with substantial soybean plantation cover, while also eliminating potentially unreliable plantation yield values from areas with the less soybean production. The researchers also interested models in research like Baseline models and Deep learning models. For transfer knowledge gaining from Argentina to Brazil, researchers began by initializing the long-term memory model using variables obtained from a balanced network practiced on Argentine soybean harvest data.

APPLICATION INSIGHTS:

Integration of Unmanned Aircraft Systems (UAS) in Agriculture:

- UAS-Based Remote Sensing Applications: Explore how UAS are utilized for various agricultural tasks, including crop monitoring, disease identification, and irrigation management.
- Potential of UAS for Precision Agriculture: Discuss the benefits of UAS technology for achieving precision agriculture, such as reduced resource wastage and increased productivity.

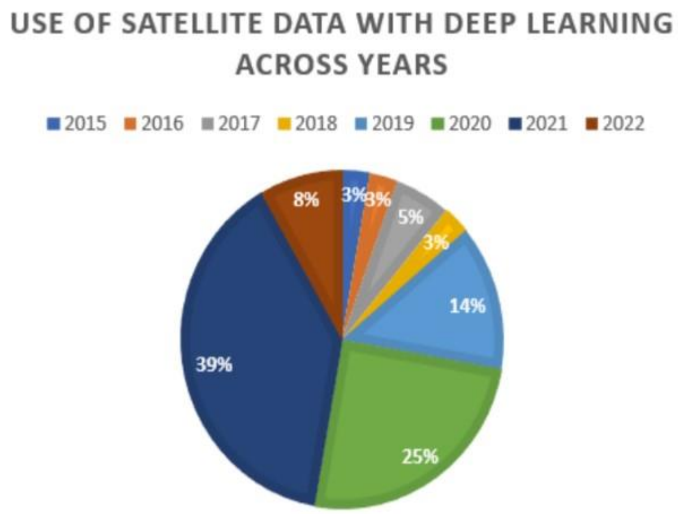


Figure 4. Distribution of articles on the use of satellite data with deep learning between 2015 and 2022.

Remote Sensing Data Integration:

- Utilization of Satellite Data for Precision Agriculture: Explain how satellite data is harnessed for large-scale precision agriculture, enabling the monitoring of vast agricultural regions.

- Crop Phenotypic Information from UAS for Satellite-based Crop Status: Discuss how data from UAS, including phenotypic information about crops, can be integrated into satellite-based assessments of crop status, enhancing accuracy and coverage.

Advancements in AI for Agriculture:

- Genomic Analysis and Crop Parameters: Provide examples of how AI is used to analyze crop genomes and predict crop parameters, including yield, disease resistance, and growth patterns.
- Impact of AI and Remote Sensing on Early Yield Predictions: Illustrate how AI, coupled with remote sensing data, can enable early yield predictions, which aid in better crop management and market forecasting.

STRATEGIC IMPERATIVES:

Standardized Protocols in Agricultural Data Collection:

- Establishing Protocols for Data Quality and Analysis: Elaborate on the need for standardized data collection and analysis procedures, including data quality control, to ensure reliable and consistent results.
- Role in Advancing Technology-Driven Agriculture: Discuss how standardized protocols are fundamental to the evolution of technology-driven agriculture, as they provide a foundation for data-driven decision-making.

Future Perspectives in Agriculture and Technology:

- Opportunities and Challenges in Data-Driven Agriculture: Examine the potential opportunities and challenges presented by data-driven agriculture, including data accessibility, privacy concerns, and scalability.

- Impacts of Remote Sensing and AI on Future Agricultural Practices: Speculate on the future role of remote sensing and AI in agriculture, predicting their influence on farming practices, crop management, and sustainability.

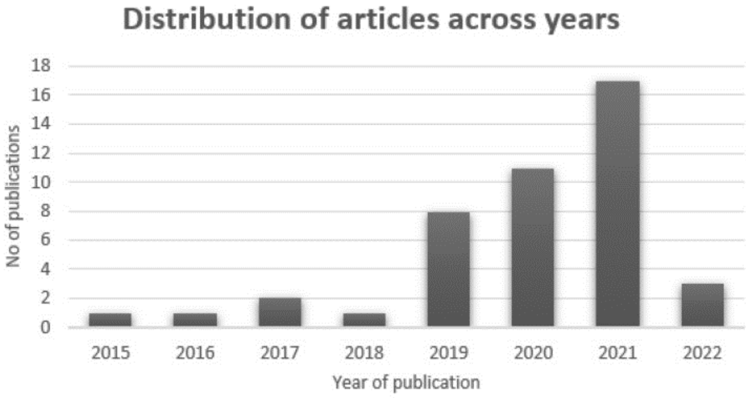
RESULTS:

In choosing the training algorithm, the study assessed three options: Adadelta, Stochastic Gradient Descent -momentum, and RMSprop. RMSprop exhibited inadequate confluence and was eliminated from further consideration. Adadelta surpassed SGD-momentum in performance, earning it the selection as the preferred practicing algorithm.

Deepest part of the Network: The study examined the impact of the depth of the CNN on the test and practicing errors for different window size and different network depth. It was found that the largest window size (40x40 meters) consistently produced the lowest test errors. The optimal network depth for minimizing test errors was determined to be 6 convolutional layers. The generalization gaps (the difference between training and test errors) were narrowed with this configuration.

Optimization of Adadelta Hyperparameters: Hyperparameters for the Adadelta schooling algorithm had been tuned, considering the habituate studying charge and the coefficient adjusting the impact of beyond iterations' errors corrections. The grid search was conducted with hyperparameter values, and the results showed that different values were optimal for early and past due RGB data sets. The optimal values were found to be approximately 8 x 10^-3 for the swotting rate and 0.58 for the accessory for the early data set and 10^-4 and 0.9 for the late data set. This tuning process improved the model's performance significantly.

Optimization of Regularization Variables: The convolutional neural network models were trained with optimal hyperparameters for the Adadelta training algorithm, and regularization parameters were tuned to assess their impact on prediction error. The tuning of weight decay coefficient was performed with a grid search and then a more focused random search.



Articles from 2012-2014 did not satisfy the selection criteria

LSTM is also widely used in crop forecasting, and its capacity to research time-structured statistics makes it different from different deep getting to know strategies methods. DNN is also used for crop yield prediction, whether individual prediction or multiple fusion prediction. In addition to the menu obtained from remote sensing in the visual text, other features like precipitation and temperature are also paired according to weather information. Similarly, properties like soil, soil ease, sieve ease, coarse soil material and sand density. Additionally, since the growth stage/phenological stage of the crop has an impact on the crop yield forecast, any change in weather conditions during the growing season will affect the growth performance of the plant, ultimately leading to changes in crop yields.

Unique Advances:

Multidisciplinary Collaboration in Agriculture:

- Importance of Collaborative Efforts in Biological, Environmental, and Computer Sciences: Emphasize the significance of interdisciplinary collaboration to address complex agricultural challenges that span genetics, environmental conditions, and data analysis.

- Achieving Synergy in Technological Innovations for Agricultural Resilience: Highlight how the integration of expertise from various fields leads to innovative solutions, and how the combination of UAS, remote sensing, and AI exemplifies this synergy.

Pioneering Developments in Agriculture:

- UAS-Based High Throughput Phenotyping (HTP) and Spaceborne Remote Sensing: Explain the cutting-edge concept of HTP using UAS and spaceborne remote sensing data for detailed crop assessments.
- Promising Future of Large-Area Digital Agriculture Applications: Discuss the potential impact of these pioneering developments in expanding digital agriculture to cover large regions, potentially revolutionizing global food production.

CONCLUSION:

This review explored the utility of deep gaining knowledge of and remote sensing in crop functioning and yield prediction. While promising, provocations like limited data, model design, generalization, and transparency must be addressed for broader use. These improvements can contribute to food security and informed decision-making in agriculture. All studies were conducted on variable types of crops, geological locations and different elements. Convolutional neural network has capacity to locate essential properties that could influence crop yield prediction. Furthermore, long-term memory now not simplest identifies the variant sample of the records, but also the dependent association of the time series data. In the face of mounting agricultural challenges, the fusion of UAS technology, remote sensing, AI, and genomic analysis offers an optimistic trajectory for sustainable food production. The necessity for standardized data practices and interdisciplinary collaborations remains pivotal for the realization of a technology-driven agricultural future. Based on this study, it was found that the most used elements are plantation indices and meteorological data, wherein vegetation indices explain crop characteristics and meteorological information help to display climatic situations that have a right way impact on crop yield forecast. The outcomes in Argentina and Brazil showcase the success of this approach in learning valuable properties from raw data, resulting in enhanced performance differentiated to conventional processes. The prospect of boosting prognostic capabilities in data-limited regions through transfer learning is promising, particularly as these areas could greatly benefit from an affordable and reliable crop prediction tool. Future endeavours should focus on extending the plea of this method to additional regions, accommodating a broader range of crops, and leveraging models pre-trained on the data-rich US to facilitate transfer learning in other countries.

REFERENCES

1. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K. Global Consequences of Land Use. Science 2005, 309, 570–574. [CrossRef] [PubMed]

2. Joseph, G. Fundamentals of Remote Sensing; Universities Press: Hyderabad, India, 2005.

3. Lillesand, T.; Kiefer, R.W.; Chipman, J. Remote Sensing and Image Interpretation; John Wiley & Sons: New York, NY, USA, 2015.

4. Wang, A.X.; Tran, C.; Desai, N.; Lobell, D.; Ermon, S. Deep transfer learning for crop yield prediction with remote sensing data. In Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, Menlo Park and San Jose, CA, USA, 20–22 June 2018.

5.Konikow, L.F.; Kendy, E. Groundwater depletion: A global problem. Hydrogeol. J. 2005, 13, 317–320.

6. Kheir, A.M.S.; Alkharabsheh, H.M.; Seleiman, M.F.; Al-Saif, A.M.; Ammar, K.A.; Attia, A.; Zoghdan, M.G.; Shabana, M.M.A.; Aboelsoud, H.; Schillaci, C. Calibration and validation of AQUACROP and APSIM models to optimize wheat yield and water saving in Arid regions. Land 2021, 10, 1375. [CrossRef]

7. Sarker, I.H. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN Comput. Sci. 2021, 2, 1–20. [CrossRef] [PubMed]

8. Gillespie, S.; Van den Bold, M. Agriculture, food systems, and nutrition: Meeting the challenge. Glob. Chall. 2017, 1, 1600002.

9. Patel, R. The long green revolution. J. Peasant Stud. 2013, 40, 1–63.

10. Pingali, P.L. Green revolution: Impacts, limits, and the path ahead. Proc. Natl. Acad. Sci. USA 2012, 109, 12302–12308.

11. Wik, M.; Pingali, P.; Broca, S. Background Paper for the World Development Report 2008: Global Agricultural Performance: Past Trends and Future Prospects; World Bank: Washington, DC, USA, 2008.

12.Bose, P., Kasabov, N.K., Bruzzone, L., Hartono, R.N., 2016. Spiking neural networks for crop yield estimation based on spatiotemporal analysis of image time series. IEEE Trans. Geosci. Remote Sens. 54 (11), 6563–6573.

13.Bottou, L., 1998. On-line Learning in Neural Networks. Cambridge University Press, New York, NY, USA Ch. On-line Le, pp. 9–42.