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Deep Learning Techniques Used in Agriculture: A Review

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Abstract: Deep learning (DL) is a kind of sophisticated data analysis and image processing technology, with good results and great potential. DL has been applied to many different fields, and it is also being applied to the agricultural field. Deep learning algorithms have revolutionized various industries, including agriculture, by enabling advanced image processing and accurate predictions. This paper explores a wide-ranging review of research papers and articles on deep learning algorithms for image processing and predictions in the field of agriculture. It analyzed works on an overview of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants, highlighting their applications in crop yield estimation, disease detection; weed identification, and irrigation management. Additionally, the paper discusses the challenges and potential future directions of deep learning algorithms in agriculture.
Keywords: convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU)

I. INTRODUCTION

The demand for food in India is rapidly expanding, yet the country faces limitations in terms of resources and arable areas. Therefore, addressing the need of food production in a more efficient and intelligent manner is crucial. Several unresolved challenges in the agricultural sector must be tracked, with crop yield emerging as a significant concern.

The growing demand for efficient and sustainable agricultural practices has led to the adoption of deep learning algorithms in agriculture for image processing and predictions. This section introduces the significance of deep learning in the agricultural domain and provides an overview of the objectives of this review paper.

Agriculture, which has been practiced for thousands of years, involves utilizing the environment to cultivate food. It is considered a primary source of employment in most countries. However, farmers historically lacked knowledge about soil types, crop yields, weather conditions, and proper use of inputs. This resulted in problems such as inefficient irrigation, crop failures, and intuitive adjustments to farming techniques. These issues were more manageable in the past due to smaller land parcels and limited resources.

However, as farms expanded and were divided into larger hectares, the need for effective monitoring and management of agricultural information became apparent. Neglecting to do so could result in new problems and increased production costs. This is where the immense potential of the latest digital technologies comes into play. The opportunities provided by these technologies have significantly contributed to the progress of agriculture towards industrialization.

Harnessing the power of data analytics, farmers can now make informed decisions regarding soil health, crop selection, optimal irrigation techniques, and overall farm management. This enables them to maximize productivity, minimize resource wastage, and reduce environmental impact.

Moreover, Artificial Intelligence empowers farmers with real-time information on weather conditions, allowing them to adjust their strategies accordingly. It also enables them to monitor crop growth and health remotely, identifying issues such as pests or diseases early on and taking immediate action.

Overall, Artificial Intelligence represents a paradigm shift in the farming industry. It allows for the integration of technology, data, and expertise to optimize agricultural production on a larger scale. By embracing these digital advancements, agriculture can continue to evolve, meet the demands of a growing population, and contribute to sustainable food production in the future.

II. RESEARCH ARTICLES SEARCHING STRATEGY

The selection process for the review articles ensured the inclusion of studies that met specific criteria related to hyperspectral imagery and crop identification or classification. By focusing on hyperspectral imagery, the review aimed to capture the use of advanced imaging techniques that provide valuable insights into agricultural practices. Additionally, the requirement to identify or classify multiple crops ensured that the chosen articles were directly relevant to the field.

To provide a comprehensive analysis, multispectral imagery was also considered alongside hyperspectral imagery. This allowed for a comparison between the two techniques and enhanced the understanding of their respective strengths and limitations in agricultural applications. By including multispectral imagery, the review aimed to provide a holistic view of imaging methods used in crop analysis.

To gather the relevant literature, a targeted search strategy was employed. Several keywords such as "images," "deep learning," "machine learning," and "application in agriculture" were utilized to identify studies focused on the extraction and classification of satellite data. This approach ensured that the review encompassed research that leveraged cutting-edge techniques and methodologies in the field of agricultural imaging.

The literature search was conducted across reputable electronic databases including IEEE, Springer, Scopus, Web-of-Science, Elsevier, and Taylor & Francis Publishers. These databases are widely recognized for hosting high-quality publications and are considered authoritative sources in the academic community. By searching these databases, the review aimed to ensure the inclusion of studies that adhere to rigorous standards of research and publication.

In total, 40 journal articles and conference papers were downloaded and included in the review. To ensure the currency of the review, only the most recent publications were taken into account. This ensured that the analysis was based on the latest developments and advancements in the field of agricultural crop analysis.

Among the selected articles, 11 reports showcased the current deep learning methods employed in agricultural crop analysis. These reports highlighted the importance of advanced computational techniques in extracting meaningful information from imaging data and contributed to a deeper understanding of crop patterns and characteristics.

Additionally, seven reports demonstrated the application of machine learning techniques in the agricultural domain. These studies showcased the potential of machine learning algorithms in analyzing large datasets, improving crop classification accuracy, and predicting crop behavior.

In addition to crop analysis, the potential of hyperspectral imaging was explored in various other applications within agriculture. This included the detection of diseases affecting crops, analysis of soil characteristics for optimal farming practices, and the mapping of biophysical and biochemical traits of crops. The versatility of hyperspectral imaging in these domains highlighted its wide-ranging capabilities and the potential for transformative impacts in agricultural research and practice.

It is important to note that all the reviewed literature was easily accessible in digital format through the official websites of the respective publishers and databases. This ensured that the information gathered for the review was readily available to researchers, enabling further investigations and advancements in the field.

Overall, the implemented approach for selecting and reviewing the articles ensured a comprehensive and up-to-date analysis of the techniques, methodologies, and potential applications of hyperspectral imaging in agricultural crop analysis and related fields.

III. DEEP LEARNING ALGORITHMS FOR IMAGE PROCESSING

This section provides a comprehensive overview of deep learning algorithms used for image processing in agriculture. It covers the basics of convolutional neural networks (CNNs) and their application in crop yield estimation, plant disease detection, and weed identification. Moreover, it explores techniques such as transfer learning, data augmentation, and image segmentation, which contribute to enhancing the performance of deep learning models in agricultural image analysis.

Deep Learning has revolutionized pattern recognition, mainly due to its effectiveness in handling vast amounts of data. Convolutional Neural Networks (CNN), also referred to as ConvNets, have emerged as the go-to deep neural network model in Computer Vision applications. The popularity of using hidden layers has surpassed conventional methods, further cementing the dominance of deep learning in the field.

Convolutional neural networks are built using several layers of artificial neurons. These artificial neurons are similar in function to their biological counterparts and are essentially mathematical functions that calculate the weighted sum of multiple inputs. They then produce an activation value as an output. In the case of ConvNets, when an image is fed into the network, each layer generates multiple activation functions. These activation functions are then passed on to the succeeding layer for further processing.

IV. DEEP LEARNING ALGORITHMS FOR PREDICTIONS IN AGRICULTURE

In this section, various deep learning algorithms used for prediction tasks in agriculture are discussed. Specifically, recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) and gated recurrent unit (GRU), are explored for tasks such as yield prediction, weather forecasting, and irrigation management. The section also highlights the advancements in combining CNNs and RNNs for joint image processing and prediction tasks.

Recurrent Neural Networks (RNNs) are a specialized type of neural network that excels at modeling and predicting sequential data. Unlike traditional feedforward networks, RNNs possess a unique ability to capture temporal information, resembling the behavior of the human brain. In essence, RNNs have the remarkable capability to anticipate and understand sequential data in ways that other algorithms typically cannot match.

In standard neural networks, all inputs and outputs are treated as independent entities. However, there are situations where considering the context of previous inputs is crucial, such as predicting the next word in a sentence. To address this, Recurrent Neural Networks (RNNs) were introduced. RNNs utilize a Hidden Layer to tackle this challenge by remembering prior information. The essential element of an RNN is the Hidden state, which stores specific details about a sequence.

RNNs possess a Memory component that retains all relevant information during the computation. It applies the same weights and biases to each input, ensuring consistent processing for all inputs and hidden layers.

The introduction of the Gated Recurrent Unit (GRU) in 2014 by Cho et al. presented a simpler alternative to the well-known Long Short-Term Memory (LSTM) networks. GRU, similar to LSTM, is a type of recurrent neural network (RNN) designed to handle sequential data like text, speech, and time-series data.

The concept behind the GRU revolves around the use of gating mechanisms, which allow for selective updates to the network's hidden state at every time step. These gating mechanisms play a vital role in regulating the flow of information into and out of the network. In the case of GRU, there are two gating mechanisms: the reset gate and the update gate. The reset gate determines the degree to which the previous hidden state should be forgotten, aiding in the management of long-term dependencies. On the other hand, the update gate determines the extent to which the new input should influence the updated hidden state. The final output of the GRU is then calculated based on this updated hidden state.

In summary, the GRU provides an efficient solution for processing sequential data by leveraging gating mechanisms that allow for controlled information flow and dynamic updates to the hidden state

V. APPLICATIONS OF DEEP LEARNING ALGORITHMS IN AGRICULTURE

This section presents an in-depth analysis of the applications of deep learning algorithms in agriculture. It explores case studies and research papers focusing on crop yield estimation, disease detection, weed identification, soil quality assessment, and water management. Each application is discussed in terms of the specific deep learning algorithms employed, dataset requirements, model architectures, and achieved results.

Traditionally, computer vision tasks were solved by feature-based manual methods in machine learning. To classify every pixel in a picture, they have typically used classifiers like Support Vector Machines (SVM). While numerous improvements have been made to the old approaches, most of them are still based on low and medium-density picture verification, and they typically require modification based on the particular scenario. Such as Chlorophyll content, Fungal diseases detection, Drought stress detection, Weeds detection and management Crop classification

VI. CHALLENGES AND FUTURE DIRECTIONS

Deep learning algorithms have shown remarkable success in agriculture, but several challenges and limitations still exist. This section discusses challenges related to data scarcity, interpretability, scalability, and computational requirements. Additionally, it outlines potential future directions for improving deep learning algorithms in agriculture, including the integration of multimodal data, addressing domain shift, and increasing explainability.

1) *Data:* Data is the most fundamental requirement to build machine learning models. Many researchers faced challenges regarding data like lack of data, unavailability of data in the required format, poor quality of data, data may contain extraneous features, etc. From this survey, it is observed that many researchers use data source sites like Kaggel, Meandly, IEEE Data port, etc. to get the data to build models.
2) *Pre-processing of the data:* As there are a lot of problems associated with data, one has to apply the different pre-processing techniques to make the data suitable for training, testing, and validation testing the model. This might be a time-consuming process such as dimensional problems, Deep learning limitations, Mixed pixel classification, etc.

VII. CONCLUSION

This review paper provides a comprehensive overview of the applications of deep learning algorithms in agriculture for image processing and predictions. Deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs) has demonstrated significant potential in addressing critical challenges faced by the agricultural industry. These algorithms have been successfully utilized for crop yield estimation, disease detection, weed identification, and irrigation management, among other applications.

The integration of deep learning algorithms in agriculture has paved the way for more accurate and efficient decision-making processes, leading to improved crop productivity, reduced resource consumption, and enhanced sustainability. The reviewed studies and case studies have showcased the capabilities of deep learning models in handling diverse agricultural data, including images, weather data, and satellite imagery.

Despite the promising results, challenges persist. The scarcity of labeled agricultural datasets, interpretability of deep learning models, scalability to large-scale agricultural operations, and computational requirements are some of the key challenges that need to be addressed. Furthermore, ensuring the robustness and generalizability of deep learning algorithms in diverse agricultural environments is crucial.

Future research directions may focus on the integration of multimodal data, such as combining image data with climatic and soil sensor data, to improve predictions and management decisions in agriculture. Additionally, addressing domain shift and transfer learning techniques can enhance model performance across different geographical regions and agricultural systems. The development of explainable AI techniques can also enhance user trust and facilitate the adoption of deep learning algorithms in agriculture.

In conclusion, deep learning algorithms have proven their potential to revolutionize agriculture by enabling accurate image processing and predictions. As research continues to advance in this field, the integration of deep learning techniques holds immense promise in addressing agricultural challenges and transforming the industry into a more productive, sustainable, and efficient domain.

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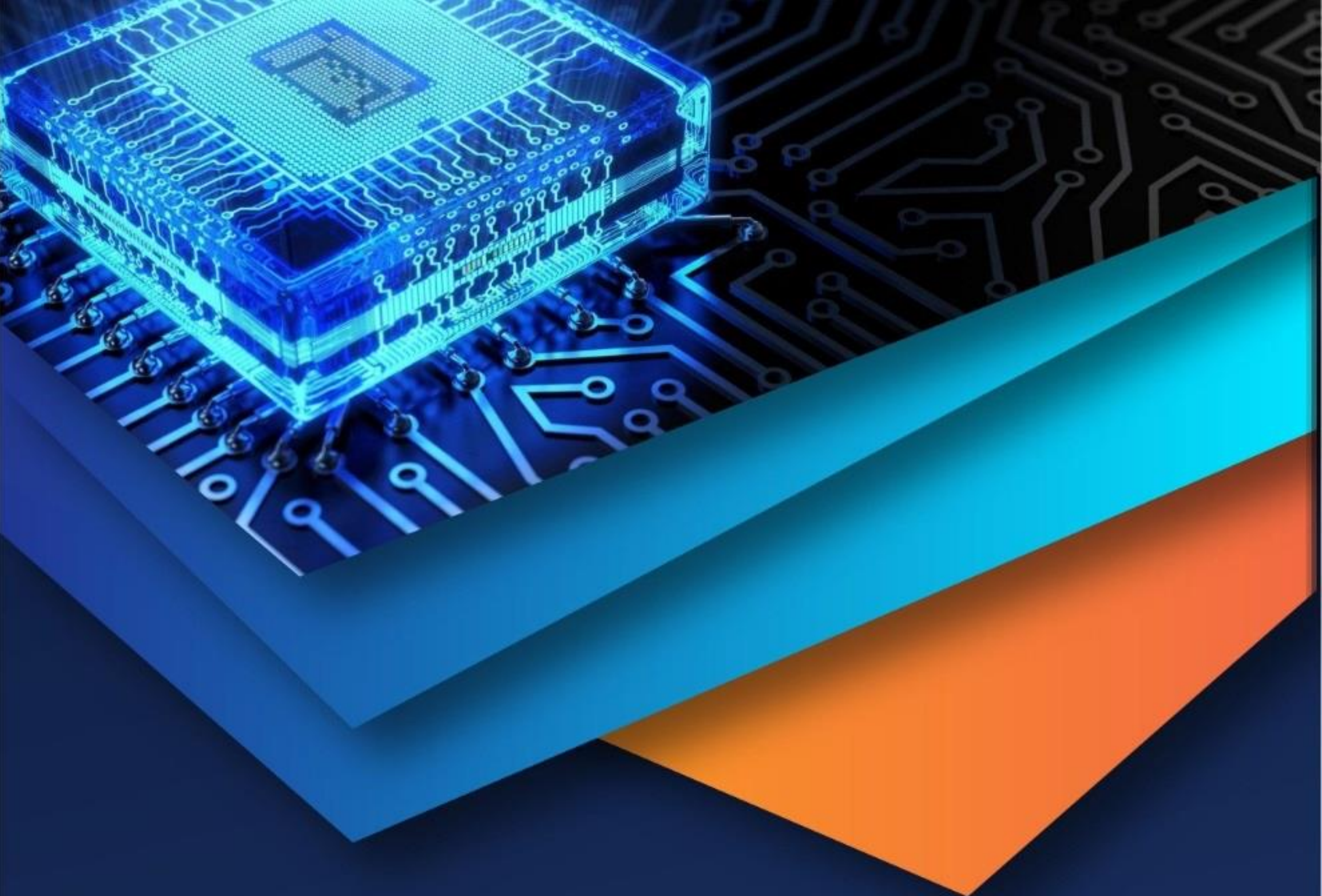

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