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Analysis of Deep Learning Models for Precise Agriculture

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Abstract: This paper presents the transformative impact of Smart Agriculture that focusing on advancements in soil properties monitoring, intelligent production strategies among climate change challenges and precision crop recommendations. Investigating the integration of Internet of Things (IoT) and Artificial Intelligence (AI) technologies, the study investigates into real-time data analytics for informed decision-making that emphasizing water requirements optimization. The review highlights the current state of precision agriculture and highlights its potential in addressing environmental concerns. Additionally, the paper discusses future prospects that predicting enhanced sustainability, resource efficiency and productivity through continued technological innovations in the field of precision agriculture.

Keywords: precise agriculture, climate change, soil properties, water requirements, crop yield, future prediction.

1. Introduction

Technological progress has brought about significant transformations across various sectors with agriculture being no exception. The agricultural domain is typically characterized by risk aversion which is undergoing a paradigm shift, striving to enhance crop yield and quality through improved crop varieties [1]. Traditional methods such as mutagenesis, gene editing, breeding and marker-assisted breeding have long been employed to diversify and enhance the genetic pool of crops. However, the agricultural sector faces challenges stemming from climate change [2] necessitating adaptations and advancements in sustainable resource utilization to mitigate environmental degradation.

The agricultural landscape confronts threats to efficiency from population pressure that evolving climates and losses in crops due to mismanagement [3]. Projections by the United Nations estimate a global population of 9.8 billion by 2050 with potential growth to 11.2 billion in the next 70–80 years [4]. To meet the escalating food demand and ensure security, a 50% increase in food production is imperative.

Smart farming is also known as smart agriculture, emerges as a solution to address these challenges by employing sustainable practices while minimizing adverse effects. Embraced globally, smart agriculture focuses on resource optimization for sustainable outputs, aiming to reduce associated costs. This approach integrates technologies such as sensors, IoT, AI and robotics to augment traditional agriculture that transforming it into a smart and sustainable system [5].

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2. Smart Farming Based Precise Agriculture

The IoT is a convergence of technologies that holds promise in providing modern solutions to agricultural issues [6]. Data mining technologies further dissect vast datasets—whether agronomic, genomic, or meteorological to facilitate informed decision-making that enhancing precision and efficiency in farming activities. Soil and climatic data are collected through sensors in smart agriculture, undergoing automated processing via modern methods like spike and slab regression analysis, machine learning (ML) [7] and time-series analysis [8]. This processed data serves as early warnings for farmers regarding impending climatic events, potential pest infestations, and the spread of diseases. Equipped with these alerts, IoT based agriculture systems that integrated with ecological sensing and assisted that empower farmers to implement an irrigation, fertilization, and pest control, through digital tools and smart applications [9].

The IoT not only aids farmers and researchers in crop production but also supports decision-making by providing comprehensive information on soil, water, pesticides, fertilizers, and manures [10]. Addressing global concerns like climate change and global warming, the IoT contributes to sustainability by concentrating on resource management and informed decision-making [11]. Moreover, it facilitates effective post-harvest management and consumer interactions.

In precision farming, the IoT is instrumental in utilizing technologies such as drones, remote sensing, livestock management, smart greenhouses, imaging and climate monitoring (figure 1). Data mining modelling are actively applied to crops, environmental conditions [12] and their management. A few advanced algorithms are furnished with more robust data for enhanced decision-making in areas such as fertilizer application, disease monitoring, yield predictions, soil moisture detection, and irrigation scheduling [13].

Recognizing the significance of these smart techniques, this study aims to summarize their latest applications including estimation of yield, fertilizer and irrigation management, disease

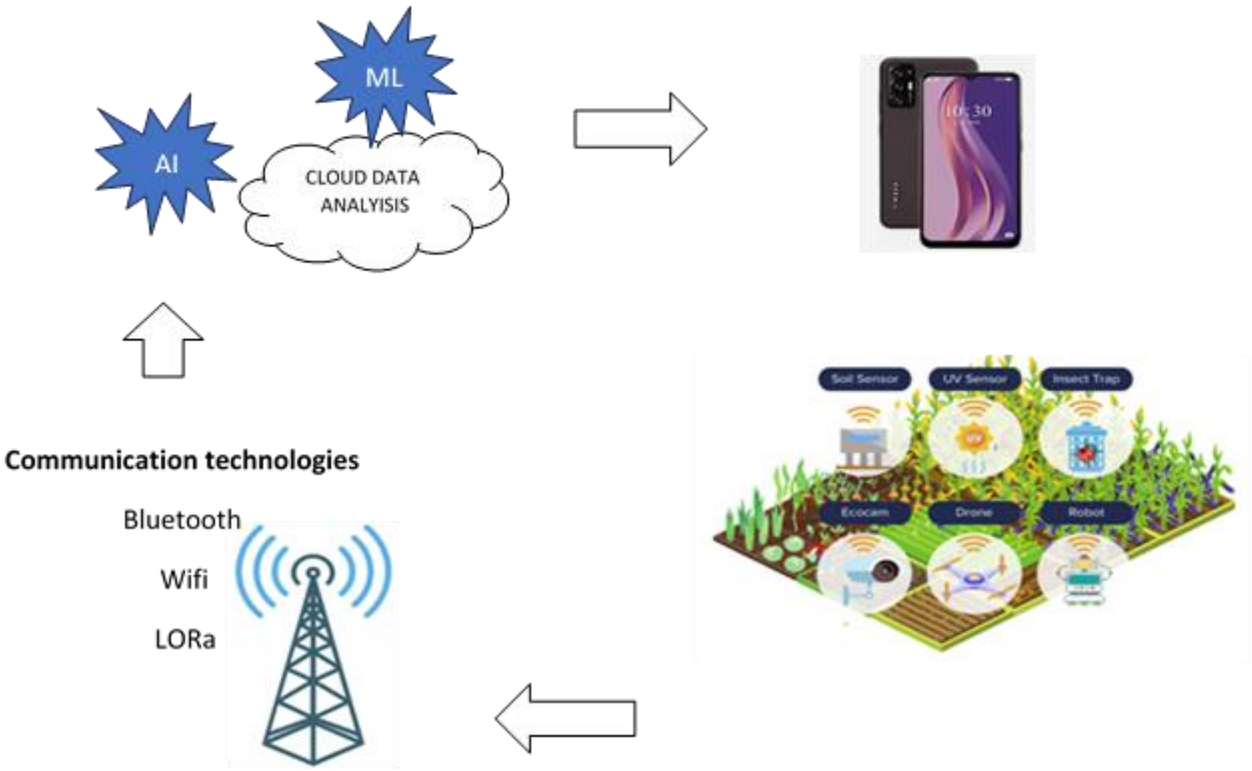

Figure 1: smart farming components and its applications

Monitoring and crop production that are especially under changing climatic conditions [14].

3. Properties of Soil

- Nitrogen (N): A vital nutrient for plant growth, nitrogen is part of the essential "Big 3 (NPK)" supplements. Plants require nitrogen the most among nutrients, playing a crucial role in protein development [15] which is essential for overall plant growth. The soil's nitrogen content is crucial in determining suitable crops for cultivation, as different crops have varying nitrogen requirements.

- Phosphorus (P): Next "Big 3 (NPK)" nutrients named as phosphorus is essential for plants' energy storage, photosynthesis [16] and overall growth and development. Like nitrogen, it needs of crops vary that making soil phosphorus values important considerations for successful crop cultivation.

- Potassium (K): As the third of the "Big 3 (NPK)" nutrients, potassium contributes to plant immunity and increased yield. It also aids in strengthening root systems, particularly in challenging conditions. Similar to nitrogen and phosphorus [17], different crops require varying amounts of potassium for optimal growth.

- pH: Soil pH is a most influencing attributes that affecting growth of the plant. pH impacts the microorganism's behaviour [18] as well as accessibility and solubility of nutrients. Most crops thrive when the soil pH is around seven, emphasizing the importance of maintaining suitable pH levels.

- Temperature: Among the primary variables in agriculture, temperature fluctuations can lead to crop failure, fertilizer inefficiency, and various other issues [19]. Optimal temperature conditions are crucial for achieving both quantitative and qualitative improvements in crop yield.

- Humidity: Indirectly linked to air temperature, humidity significantly impacts crop production. Excessive humidity can result in root diseases that improved pesticide costs and minimised yield [20]. Conversely, minimum humidity leads to sluggish growth and increased leaf drop in plants.

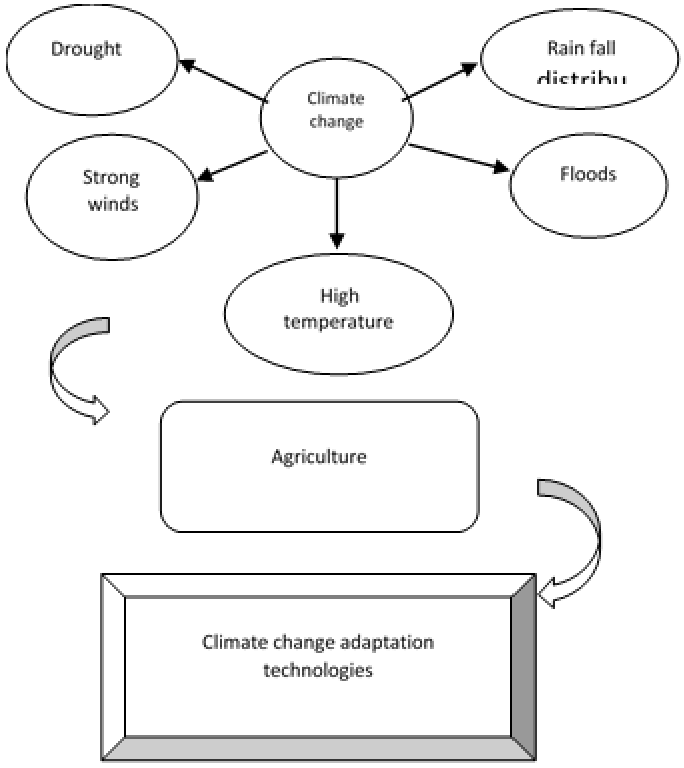

Figure 2: Climatic change adaptation Technologies

- Rainfall: It is profoundly influencing crop production which is an essential environmental factor [21]. Insufficient rainfall can deprive crops, necessitating increased artificial watering and escalating production costs. Conversely, excessive rainfall may lead to crop inundation or reduction of pesticides and fertilizers that rendering crops susceptible to diseases.

- Crop: The dataset provides specific data about crops such as rice, concerning the aforementioned seven attributes [22]. Given that most crops have acceptance ranges for each attribute, the dataset includes multiple entries per crop to account for these variations.

4. Smart Crop Production during Climate Change

The global agricultural landscape is grappling with the severe repercussions of climate change [23]. Escalating temperatures, erratic day-night temperature fluctuations, and unpredictable rainfall patterns have intensified the frequency and severity of droughts and flash floods [24]. This climatic shift has also contributed to a surge in the incidence of diseases [25]. The efficiency of production systems has been compromised, necessitating a strategic response to climate change impacts, thus emphasizing the crucial need for climate-smart adaptation measures. These adaptive strategies are essential to withstand agricultural efficiency and ensure accessibility through the year [26].

Adaptation measures must span various factors of crop production namely dynamics of soil–water, nutrient and fertilizer management. These factors enhances in crop evaluations, utilization of organic adjustments in soil and advancements in fisheries, livestock, fowl and farm mechanization as illustrated in Figure 2. As temperature emerges as a critical determinant in crop production, the adoption of smart technologies becomes increasingly imperative to mitigate the challenges posed by a changing climate [27].

5. Causes of Climatic Change

The fluctuations in temperature, attributed to both natural phenomena and human activities, serve as a catalyst for the concentration of greenhouse gases (GHGs) on Earth [28]. Anthropogenic activities particularly the emission of GHGs like CO_2, nitrous oxide, methane alongside ozone depletion contributed to environmental challenges [29]. Elevated CO_2 levels in the atmosphere impacts soil bacterial activities that influencing water content and triggering nitrous oxide and methane emissions from wetlands and upland soil respectively. This phenomenon counters the predicted 16.6% justification effect of climate change projected by growing global carbon sinks [30].

The agriculture sector plays a substantial role in contributing to total emissions, primarily through the release of methane and nitrous oxide. Predictions indicate a potential increase in global non-agricultural greenhouse gas emissions until 2055 if dietary preferences and food energy consumption remain constant at 1995 levels. Shifts towards high-value foods like meat and dairy are anticipated to escalate emissions even further [31]. Mitigation strategies involving technological interventions or reduced meat consumption, or a combination of both, can curtail emissions [32]. Notably, the livestock is an emitter of greenhouse gases that accounting for 8–10.8% based on IPCC and potentially up to 18% based on lifecycle analysis [33]. Also, livestock sector included an enteric fermentation, liming, fossil fuels, emissions of N2O, fertilizer production and organic farming. The nitrogenous chemical fertilizers used to emissions of greenhouse gas [34].

Effective management of crop production offers avenues for emission reduction. By optimizing nitrogen fertilizer use, emissions can be lowered by 38%. Improved crop management not only reduces input energy consumption by 11% but also increases yields by 33%, resulting in a 20% reduction in greenhouse gas emissions [44].

Malhi et al [36] provide a climatic change in agriculture survey that exploring its causes, projections, and impacts on agricultural physiology, metabolic activities of plants, productivity, mitigation strategies and pest infestation. King et al [37] utilized a growing degree day to assess the global northward shift under 21st-century changes in rainfall and potential evapotranspiration. Kukal et al [38] evaluated on sorghum, maize and soybean yields that emphasizing the need for resilient agricultural practices. Aryal et al [39] offered an impacts of climate on crop production and available adaptation options that highlighting the necessity for strengthened institutional setups. Navarro-Racines et al [40] present a global climate database developed using the delta method, addressing model biases. Sun et al [41] analysed a no-till-induced changes in soil carbon and crop yield that highlighting benefits in arid regions. Skendžić et al [42] explore the effects of rising temperatures and CO2 levels on insect pests that anticipating shifts in population dynamics. Datta et al [43] presented an Indian farming large-scale investments sector and advocate for an integrated approach to assess farmers' perceptions and adaptations to changing climatic conditions.

6. Crop Recommended Based on Soil Properties

Crop recommendation is a critical factor for agriculture countries like india where multiple crops can be cultivated in a one season [44]. Currently, farmers rely on their knowledge to choose crops for plantation, but this manual selection may not always result in optimal production. Inconsistencies in yield can have detrimental effects on the country's economy. Additionally, the government requires accurate predictions to estimate crop amounts for the upcoming year [45]. To address this, an ensemble machine learning (ML) model is designed to predict crop production, taking into account environmental factors, cultivation area, and previous production parameters [46].

Madhuri et al [47] employed an Artificial Neural Networks (ANN) for suggesting crops based on soil properties, climate parameters and crop behavior. The model achieved a high accuracy of 96% with ANN compared to 91.5% with decision tree that indicating the efficiency of the ANN model.

Akulwar et al [48] presented an identification of crop conditions, disease detection, crop-specific predictions and recommendations using ML model. It provides insights into how recommender systems are utilized for disease and crop prediction.

PANDE et al [49] explored a farmer's friendly mobile application for connectivity. The system utilizes several ML algorithms but Random Forest showed the best results with 95% accuracy all the among.

Mythili et al [50] developed a Deep Convolution Neural Networks (DCNN) and Long Short-Term Memory (LSTM) networks with ant colony optimization for crop predictions. It is aimed to enhance the accuracy of predictions.

Chakraborty et al [51] assisted farmers in crop selection based on sowing season, geographical location and soil. The ANN model achieved an accuracy of 89.88% that aiding farmers in choosing high-yield crops.

Garanayak et al [52] predicted a future production of crops using ML approaches in the Andhra Pradesh region. Several ML models are used and random Forest achieved a n effective result in crop production forecasting.

Sharma et al [53] focused on crop recommendation system using various ML and DL techniques based on several parameters that informed a farmer regarding crop selection.

Moon et al [54] employed a K-nearest Neighbor Random Forest Ridge Regression (KRR) to predict major crop making. The model demonstrates high accuracy for various crops, showcasing its effectiveness.

Mundada et al [55] used a hybrid LSTM and evolutionary algorithms known as enhanced LSTM for crop yield prediction. This model outperforms other ML models with an accuracy of 85%.

SSL et al [56] utilized clustering algorithms along with the Deep Q Network and k-Nearest Neighbor (KNN) to expose hidden patterns. This data is then converted into usable information for climate prediction and categorization.

Apat et al [57] present a Cat Boosting model and applied the SMOTE data balancing model to attain better results. This model performs exceptionally well with high accuracy and precision.

Parameswari et al [58] discussed a decision tree, Support Vector Machine and Recurrent Neural Network (RNN) for anticipating harvest and increasing profitability for farmers. The results show promising future perceptions based on the obtained outcomes.

7. Water Management In Precise Agriculture

Precision irrigation stands as a distinctive and sustainable agricultural methodology that focused on water and nutrients to plants at precise times and locations in measured doses to ensure an optimal crop growth [59]. Precision water management (PWM) complemented this by emphasizing judicious water use to achieve sustainable water management [60] that requiring precise application at the right time, place and crop growth stage consistently across the designated area.

Garcia et al [61] contributed to water allocation model that framing the multi-area irrigation system as a challenge of resource allocation. The dynamic priority and feedback scheduling models are employed to treat a water consumption as the primary optimization parameter.

Pincheira et al [62] developed an IoT based sensing that virtuous behaviours in agricultural practices by retaining forced sensing devices as trustworthy data sources.

Remote sensing, geophysics, and agro-hydrological modeling are explored by Pradipta et al [63] which is used to provide lateral distribution information, investigate sub-surface soil, and overcome data limitations in irrigation water scheduling for precision agriculture.

Kamienski et al [64] presented the SWAMP model that assessing the platform's scalability and replicability for IoT applications. The designed configurations and re-engineering of components provided an effective performance for SWAMP model.

Nova et al [65] address water safety through contaminant identification, pollution monitoring, and early detection of waterborne diseases. Drought prediction employed ML models based on climate data, satellite imagery and meteorological data. Smart water grids influence real-time data to optimize water distribution networks which reducing water loss.

Abioye et al [66] developed RNN models for sustainable irrigation management, highlighting digital farming solutions for smart irrigation processes. They discuss the challenges and future directions of research, emphasizing the role of remote monitoring and control in reducing stress for farmers and researchers.

Vianny et al [67] utilized LSTM, KNN Gradient Boosting and Spearman's rank correlation to predict an irrigation. These methods predict consolidated time series values by gathering nearest sensing information, predicting real values, and assessing correlations.

Akensous et al [68] surveyed a IoT and ML in agriculture that emphasizing their potential to advance the field. It explored the virtual water model to address water scarcity and essential components for effective smart irrigation with a sustainable digital agriculture model.

Elbeltagi et al [69] compared a several algorithms where Random Forest model outperforms other models in terms of certain metrics during the testing stage.

Bakthavatchalam et al [70] utilized a combination of multilayer perceptron rules-based classifiers, JRip and decision table classifiers to predict high-yield crops in precision agriculture. Their approach integrates IoT and agricultural measurements that achieving a commendable performance of 98.2273% as evaluated by selected classifiers.

Chandra et al [71] automated the labor-intensive process by using microcontroller-based system for smart drip irrigation that predicting the precise water needs of crops. This system guided by weather, soil and crop parameters to forecast the appropriate amount of water to be distributed through drip irrigation using sensors. This method effectively regulates soil moisture in the cultivation field.

Brar et al [72] facilitated by subsurface drip irrigation and fertigation models that demonstrated approximately 30% water savings due to reduced drainage losses. Furthermore, the 'summer mungbean – maize – wheat' cropping system showed increased net returns for farmers compared to conventional flood irrigation methods.

Gupta et al [73] explored Subsurface Drip Irrigation (SDI) effects combined with nitrogen management-based maize-wheat systems (MWS). The results indicated significantly higher grain yields for maize, wheat and MWS in the SDI with 100% recommended nitrogen that showcasing improvements of 15.8%, 5.2%, and 11.2%, respectively.

Abuzanouneh et al [74] designed artificial algae algorithm (AAA) in conjunction with the least squares-support vector machine model to determine an irrigation need. It is demonstrated a superior performance and achieved a maximum accuracy of 0.975.

Singh et al [75] developed a long-range, low-power (LoRa) system for IoT based ML model. It includes the soil and weather conditions to predict crop water requirements with the linear discriminant analysis model achieving the highest efficiency at 91.25% prediction accuracy.

8. Future Scope

The future scope of precise agriculture prediction using a novel cascade trio GRU (Gated Recurrent Unit) model holds tremendous potential in enhancing agricultural efficiency, water resource management and crop recommendation. In the proposed cascade trio GRU model for precise agriculture prediction, the feature extractor comprises three GRU units. The first GRU unit captures long-term trend features, while the second focuses on short-term change features. The outputs of these two units are concatenated and fed into the third GRU unit to generate site-specific features. This enhances the network's ability to characterize agricultural conditions effectively. Here's an exploration of its functions and potential benefits:

Efficient Water Resource Management: provided an efficient use of water resources that reducing the environmental impact and operational costs associated with excessive water use.

Timely Intervention for Scarcity: quickly identify water scarcity conditions and helped farmers implement mitigation strategies and minimize crop losses.

Reduced Wastage and Environmental Impact: Optimized irrigation schedules lead to reduced water wastage for an environmental sustainability with water conservation efforts.

Precision in Crop Recommendations: precise recommendations lead to better yield outcomes and economic benefits.

Continuous Improvement: adaptive in nature continuous improvement as it learns from new data that making it a valuable tool for long-term agricultural planning and decision-making.

Therefore, novel model of cascade trio GRU model is applied for a precise agriculture which has an ability to leverage advanced DL architectures for accurate PWM predictions, timely scarcity identification and informed crop recommendations. This approach contributes to sustainable and efficient agricultural practices, addressing challenges related to water management and enhancing overall crop productivity.

9. Conclusion

In this work, the comprehensive review examined an intersection between precise agriculture based on its smart agriculture, climate change, crop recommendation and water requirements. The analysis underscores the significance of integrating advanced technologies including IoT and ML to enhance precision in agricultural practices. The consideration of climate change as a pivotal factor in decision-making processes emphasizes the need for adaptive strategies in agriculture. The exploration of crop recommendation systems highlights the potential for data-driven approaches to optimize crop selection based on environmental conditions and historical data. Also, the review underscores the critical role of precise water management in agriculture, with a focus on efficient resource utilization and sustainable practices. Based on the findings of this survey, the potential of advanced models like the cascade trio GRU in providing accurate and insightful predictions. Looking ahead, the identified methodologies and insights pave the way for further advancements in precision agriculture that contributing to sustainable practices and improved decision-making in agricultural management.

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