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Assessing Climate Change Effects and Enhancing Crop Yield Predictions through Artificial Intelligence

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ABSTRACT

Climate change has lasting effects on the productivity of agriculture worldwide, thus threatening food safety and economic stability. The aim of this research is to identify how artificial technology can assist with assessment of climate change and prediction of better crop yields. By using this massive computer learning model, it is possible to yield forecasts that can analyze a variety of climate patterns, soil conditions, and crop characteristics with a precision of much higher value than that of manual input methods. Through the provision of vital information on how to prevent or mitigate disasters based on the weather forecast, AI can help farmers and decision-makers take the right decisions. In this investigation, the most recent techniques, and some cutting-edge AI applications will be presented to support their role in the changes of agriculture in the era of climate change as well as the ways in which they can be of significance in the maintenance of crop productivity. The results indicate AI's crucial contribution regarding the advancement of resilient agricultural production systems, which are able to withstand the environment's volatility and at the same time, fulfill the food needs of the world's increasing population.

1. INTRODUCTION

The modern era is overwhelming the world with its challenges, of which climate change is the most challenging [1], [2], [3]. The term "climate change" refers to extreme ascending temperatures and dissolved precipitation that have on global ecosystems, which affects agriculture directly [4]. Due to the rise in global temperatures, shifts in precipitation patterns, and struggles against extreme weather events that come with higher frequency, food production systems are at an increasing risk. Agriculture, which is the backbone of food security, economic development, and rural livelihoods is very sensitive to climate change. The traditional farming practices we used to adopt that assured bumper ends now the impact of uncertainty such as unfavorable weather conditions, soil erosion, and pests. This has resulted in a paradigm shift that has put more emphasis on the use of modern agricultural technologies in the management of crops and the optimization of crop yields [5], [6].

In such a context, Artificial Intelligence (AI) emerges as a transformative tool, offering innovative solutions to navigate the complexity of climate change [7], [8]. AI systems can generate predictive models using vast amounts of data, including historical weather, satellite photos, and real-time environmental sensors, respectively, thus enhancing the decision-making in agriculture. It involves not merely the technology of the future being utilized, but the art of resilience through the development of technology, that makes a unique solution for crop production resilient to changes in climate [9], [10].

Climate change and agriculture demand an urgent and concentrated response to be able to promptly adopt more robust and climate-resilient farming practices [11], [12]. AI provides such a pathway by offering precise agricultural solutions that are able to improve efficiency and enhance yield forecasts. Time series forecasting methods are used on historical data to provide optimal planting schedules, crop growth stages, and the most probable event that will trigger crop growth. Other areas include estimation of inputs of production, so that the producer can be guided to use resources efficiently and the management of the enterprise and strategic decisions so that the enterprise can cope with the external environment. The use of such predictive capabilities is not a long-term aiming of food production but rather a quick and accessible approach to it, especially in regions where the lack of upgraded scientific knowledge explains most of the unsustainable practices [13], [14].

Additionally, the innovations that AI drives go far beyond basic yield predictions. They help to determine soil health, optimize irrigation schedules, detect diseases or pests early on, and apply fertilizers and pesticides in a very accurate manner. Such technologies, by minimizing waste and improving their efficiency, are not only boosting crop productivity by doing so but they are also contributing to the appetite for sustainable agricultural practices by minimizing the footprint of farming on the environment [15], [16].

The application of artificial intelligence in agriculture is a cross-disciplinary approach that brings knowledge of climate science, agronomy, data science, and systems engineering into play. Such a teamwork effort is the core of creating coherent approaches to the range of problems that climate change imposes. Governments, agricultural bodies, and the private sector are increasingly acknowledging the relevance of AI in the sustainable establishment of the food supply chain. Consolidated actions and investments in research and technology infrastructure are the basis for even wider application of AI in agriculture [17].

The potential of AI notwithstanding, its application in agriculture is accompanied by obstacles. Availability and quality of data, technological infrastructure, and the digital gap between the developed and the developing world are major impediments. There are also doubt and fear around the cost and accessibility of AI technologies for smallholder farmers, who make up a large part of the global agricultural workforce. Since various parties will need to work together using publicly available data to combat these impediments, it is essential that this information is disclosed to the public. Moreover, investment in digital literacy is indispensable. Last but not least, we should enact legislation that would promote equitable access to technology.

1.1. Objectives:

- To determine how we can leverage the power of AI technologies in predictive analysis of crop yields while also a thorough assessment of climate change effects on crop yield.
- To understand how AI could be embedded in environmentally sustainable agricultural practices through, for example, improved resource use and the progressive methods of farming in nature.

In conclusion, the application of AI technology to agricultural practices is a promising strategy for reducing the adverse effects of climate change on crop production. AI will help farmers prepare for climate uncertainties in the future, through accurate yield forecasting and smart resource management, two huge benefits of the technology in sustaining global food production. If investment, research, and cross-sector collaborations are continued, these technologies will be made, tested, and scaled for crops on any size farm, commercially available. AI in agriculture not only represents humanity's technical capabilities but also reflects the crucial part of the global movement for food security and agricultural sustainable development.

2. LITERATURE REVIEW

Recently, Artificial Intelligence has emerged as a hot topic in the agriculture sector, especially in the domains of crop yield forecasting and climate change impact assessment. The AI systems are gradually replacing the old agricultural methods due to their lack of data-driven insights. The AI systems are supporting the decision-making process, increasing production, and making agriculture practices more climate-friendly. This literature review aims at drawing a portrait of the current research in this discipline by showcasing key contributions made at different times by distinct studies either of invention or of the use of

AI technologies in the agricultural sector for the evaluation of crops and climate change in agriculture systems. Rather than only a theoretical assessment of the number of studies, the review will point out the prior occurrences and the patterns of research, gaps in knowledge, and future possible study which are likely to produce a better understanding, clearer insights, and a more practically applicable outcome.

Sidhu et al. [18] investigated the application of machine learning methods in crop yield prediction and the evaluation of climate change impacts on agriculture by contrasting Boosted Regression Trees (BRTs), the present leading approach, with conventional Ordinary Least Squares (OLS) regression. The researchers highlighted that, despite being the standard technique for modeling the relationship between crop yields and weather factors for many decades, traditional linear regression is limited, while machine learning methods, especially, neural networks can provide extremely accurate forecasts. The findings from their research indicated that BRTs were more effective than the linear regression model in assessing crop yields, helping to reveal the primary points of interaction between production and climate, which remained undetected by the conventional methods. Furthermore, BRTs were able to incorporate the effects of spatial water availability and simultaneous weather events on crop yields, which was never done by others, and offered a better understanding of the effects of these variables on crop yield by household data. In how well past weather data from crops like rice, wheat, and millet in the Indian subcontinent could be applied, such a study revealed that with the help of BRTs a smaller loss than that of the linear regression method was predicted. The study also pointed out a difference in the potential opposite side of the BRT technology's advantage—the danger of implicating weather and time in such regions is a specific console that has tremendously different climatic and agricultural conditions. Thus, special care given to the choice of machine learning tools is necessary so as to be able to interpret the results qualitatively, as they can eventually establish the link between climate change and agricultural productivity.

Crane-Droesch et al. [19] analyze the connection between climate, agricultural outputs, as well as the impacts of climate change on food production, revealing a groundbreaking modeling strategy that makes use of a semiparametric version of a deep neural network. This approach allows one to correctly capture the various crop yields with the help of casual relations, which are nonlinear and through the use of high-dimensional datasets. The authors incorporated well-established pre-parametric models and unobserved cross-sectional heterogeneity into the language model in order to improve the accuracy of crop yield prediction with respect to the combination of the two previously mentioned methods, especially for real time study. Moreover, the paper adopts different climate scenarios to predict the reduction of corn yields due to climate change. The results show that although climate change affects negatively crop yields, using the semiparametric method will generally be less damaging than applying traditional statistical approaches. For anthropogenic warming scenarios, instead of bitumen light source, the semiparametric model produced the highest optimistic forecasts which are again the recognition of the contribution of advanced modeling techniques to the production of more precise, farmers-friendly agricultural predictions. The research adds to the increasing body of evidence promoting the combination of models and flexibility as the best way to looking at the climate variability-agricultural outcomes relationship.

Sarr et al. [20] explored the agricultural field in Senegal in terms of economy that is, with the uptick of the impact of climate change on crop yields. The authors compared the effectiveness of three approaches, namely, support vector machines, random forests, and neural networks – as well as one multiple linear regression technique known as Least Absolute Shrinkage and Selection Operator (LASSO) in predicting key staple crops, such as peanuts, maize, millet, and sorghum, in 24 departments of Senegal. The authors were also interested in three other factors: climate data, vegetation data, and a hybrid of both to test the contribution of each predictor to the accuracy of the predictions. As the results show, applying machine learning algorithms to the datasets followed by an outer climate-data unit gave rise to the most accurate predictions of all and notably also determining peanut production, being one sensitive to weekly climatic variants, efficiency of that method. They point out the urgent requirement of further research work to apply the proposed systems to food safety systems currently being applied. At the same time, this research gives strongly convincing evidence that machine learning can be used for yield forecasting. The ultimate goal of developing such systems is to facilitate Senegal's capabilities to adapt to climate change thus farming security in the area. This research exemplifies the significance of sophisticated statistical techniques for better agricultural planning and management in the environment of developing areas adapting to climate variations.

Li et al. [21] focused on the effects of climate change on crop yields and criticized conventional models for merely considering the main factors of crop growth and ignoring critical events like drought and pest invasions. To address this limitation, the researchers integrated the outputs of nine global crop models with the random forest algorithm to get the results and provide more accurate projections for maize and soybeans in China. Their model showed a substantial increase in accuracy with the uncertainties being reduced from 33 to 78% by maize and from 56 to 68% by soybeans. The model includes determinates like cool days, pest invasion, disease, and drought. As a result, it becomes more and more inclusive and accurate in the forecasts of harvests.

Aworka et al. [22] thoroughly looked into East Africa's lack of food security, the cause of which is the changing climate that poses serious threats to farming. At the present time, the United Nations has set the goal of eliminating hunger by the year 2030, and therefore, the development of more efficient management tools will be a top priority. The authors created three machine learning techniques, which are as follows: Crop Random Forest, Crop Boosting, and Crop Support Vector Machine. Those models were created with the available data such as climate, production, and pesticide use from 14 East African countries. The results are showing that these models are reliable in terms of the prediction of crop yields because they have high R^2 values and low error rates. The results indicate the possibility of applying these models by both decision-makers and farmers in order to raise performance and ensure food security in the context of climate change. Machine learning has proven to be a very effective means to deal with data gaps and thus, improve the agricultural output in the East African region.

Table 1 : Literature Review Comparison

Study	**Objective**	**Methods Used**	**Key Findings**	**Implications**
Sidhu et al.	Predict crop yields and assess climate change effects on agriculture using machine learning	Comparison of Boosted Regression Trees (BRTs) and Linear Regression (LR)	BRT outperforms LR, providing deeper insights into climate-yield relationships by accounting for spatial fluctuations and climate interactions.	BRTs improve forecasting accuracy and offer better insights into the impact of climate change on crop yields.
Crane-Droesch et al.	Explore the relationship between weather, crop yields, and climate change effects on agriculture	Semiparametric deep neural network model	The model forecasts crop yields more accurately than traditional statistical methods, particularly for forecast years not included in training.	Advanced modeling techniques like semiparametric neural networks provide more precise agricultural forecasts in changing climates.
Sarr et al.	Forecast crop yields in Senegal while considering climate change	Machine Learning (SVM, RF, NN) and LASSO regression, with climate and vegetation data	Machine learning models combining climate and vegetation data performed best, with peanuts being the most accurately predicted crop.	ML models can improve crop yield forecasting and help develop climate adaptation strategies for food security in Senegal.
Li et al.	Address climate-	Integration of nine	Enhanced accuracy of	Incorporating a variety

	related challenges for crop yield predictions in China	global crop models with a random forest algorithm	maize and soybean yield predictions, reducing uncertainties by up to 78% for maize and 68% for soybeans.	of factors (e.g., pests, weather extremes) into models leads to more accurate crop yield forecasts.
Aworka et al.	Improve food security in East Africa by predicting crop yields amidst climate change	Machine learning models (Random Forest, Boosting, SVM), using climate, production, and pesticide data	The models provided accurate predictions, with strong R^2 and low error rates, aiding decision-makers and farmers in boosting productivity and food security.	ML can fill data gaps and enhance agricultural productivity in East Africa, supporting efforts to combat hunger.

3. PROPOSED METHODOLOGY

To discuss the various ways in which climate change affects crop yields and to use the data collected by AI to predict any progress, a totally robust methodological framework is employed in this study. The methodology is the one planned to systematically merge data collection, processing, and model development to acquire precise and appropriate predictive insights. The process has several critical stages, such as data acquisition, data preprocessing, model selection, training, validation, and deployment.

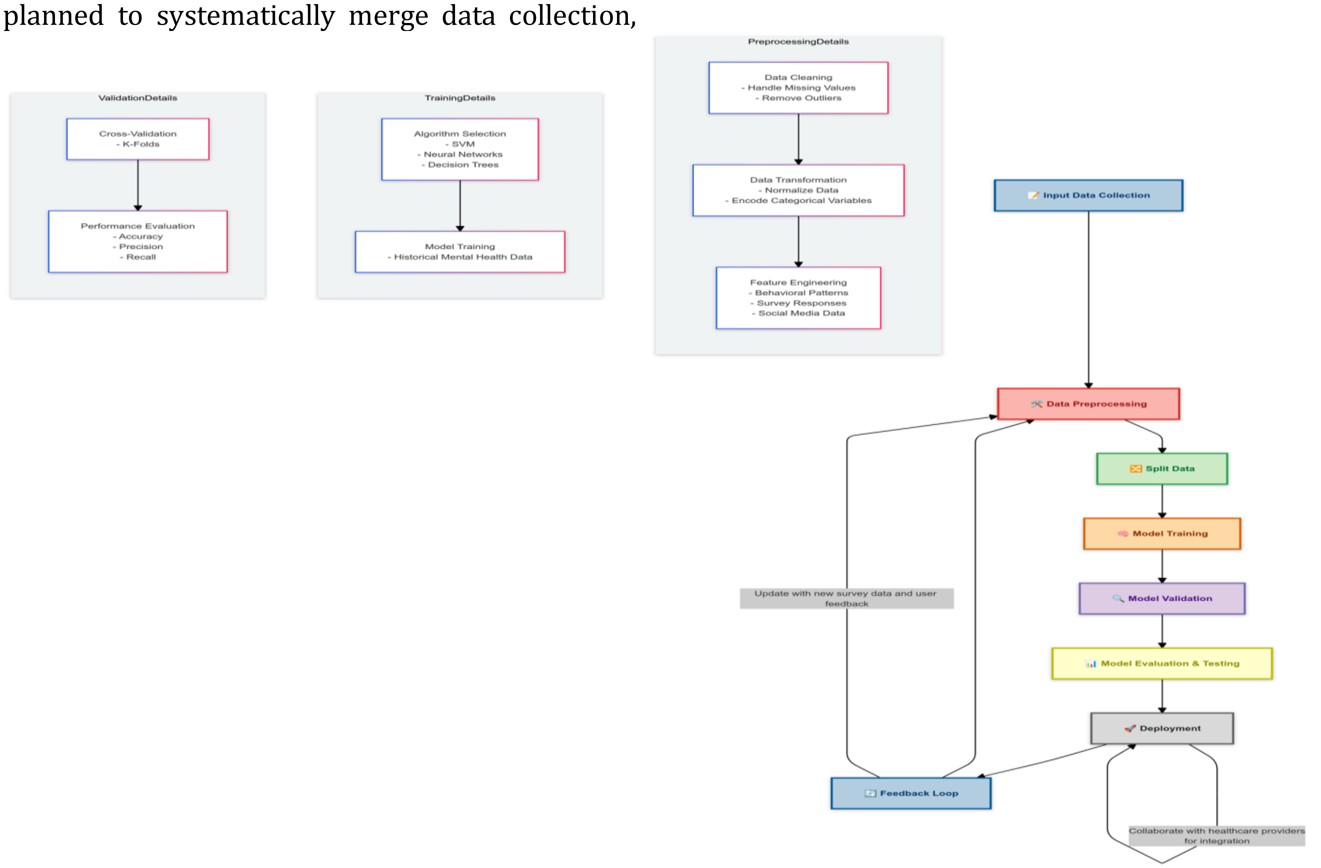

Figure 1: Working of the proposed model for crop yield prediction

The initial phase of this study is characterized by the gathering of the relevant information from different sources. Historical climate records, satellite imagery, soil health data, and reports on crop yield were utilized. The dataset was obtained from reputable organizations such as NASA, NOAA, and local agricultural departments. There was a good amount of data to assess environmental conditions, past yield, and geographical distribution of crops in agricultural sectors. The integration of data from numerous years provides an analytical longitudinal view that includes the usual climate variability's impacts on changes and those unusual ones.

Data preprocessing is that critical, initial stage, which guarantees the reliability of the raw data collected. This part also comes with the activation and correction of damaged, old, and unusual values to form the complete data set. Data normalization and transformation procedures are factored into the uniformity of the input facilitating the simple integration of the artificial intelligence model. To further increase the spatial-temporal analysis's accuracy, geographic information system (GIS) will have matching done on geo-spatial data. This data preprocessing phase is a key one in the problem of crop yield to ensure that the input data responds truly to the environmentally complex features.

The heart of this methodology involves the creation of a machine learning model that can forecast future crop yields based on the analysis of past data and present climate indicators. In this study, a combination of supervised learning models, specifically Random Forests and Gradient Boosting Machines, is applied. These methodologies were chosen because of their competence in managing the high volumes of continuous data and their capability to identify nonlinear associations between the input and output. Among the feature selection techniques were taken into consideration the most promising predictors, temperature fluctuations, precipitation patterns, soil moisture levels, and crop phenological stages.

Having defined the structure of the model, the process of training commences. The data is partitioned into controlled and experimental sets ensuring that part of the data is kept for checking the model. The assessment is based on the cross-validation combo especially k-fold cross-validation that is utilized to verify the validity of the model and the avoidance of overfitting. During the course, the hyperparameter tuning is being done by means of grid search strategies hence ensuring optimal model parameter settings with superior predictive accuracy. This mechanism of repeating the same process is key when it comes to the fine-tuning of the model as well as assuring its adequacy across different crop types and regions.

The next step in the process is model validation, where the predicted yields of the model are compared to actual yield data. Performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and R-squared metrics are calculated so as to assess predictive accuracy. The validation session with commendable performance signifies that the model possesses a good external generalization capacity thus it can be successfully applied for reliable yield predictions on new data sets. To understand the model's behavior with respect to alterations in input variables, sensitivity analyses are carried out thereby firming up the model under different climatic scenarios.

The machine learning rehabilitation of crops is the very last stage of the technology deployment process. The forecast in crop management is after making it possible to the users to download machine-learning-based decision-making software, the system for users of that model is a friendly one because such people as farmers and authorities can get into the predictive insights in addition to the decision-making process on crop management. The system is set up to create alerts in real-time on detrimental weather events, proposals for planting and harvesting windows, and pointing to the best allocation of the resources. This implementation of this application is one of the main reasons AI can change farming practices and help the environment recover from the consequences of climate change.

Figure 1 illustrates the flow of activities contained in the AI/Predictive Framework and also indicates how the system will work in responding to the various situations. The first stage is an import of preprocessed variables, which is followed by the feeding of these inputs into the machine learning algorithms. The generated predictions of the yield are the outputs evaluated against previously known benchmarks that secure precision and reliability. The proposed model not only polishes yield forecasts but also suggests an integration formula in various climates and crops under cultivation through this layered plan.

4. SIMULATION RESULTS

The implementation of advanced machine learning systems led to different levels of accuracy and effectiveness when it comes to predicting crop yields. The datasets we obtained from Kaggle [23] were primarily used to identify the parameters that were critical in modeling plant yield. We have not only trained machine learning systems but also added weather data and production statistics as precursor variables to identify the connections that scientists used in experiments to allow machine learning analysis. Figure 2 compares the performance of Random Forest, Gradient Boosting, and Support Vector Machine models. The Random Forest model stood out as the most competent one, scoring an R^2 value of approximately 0.82.

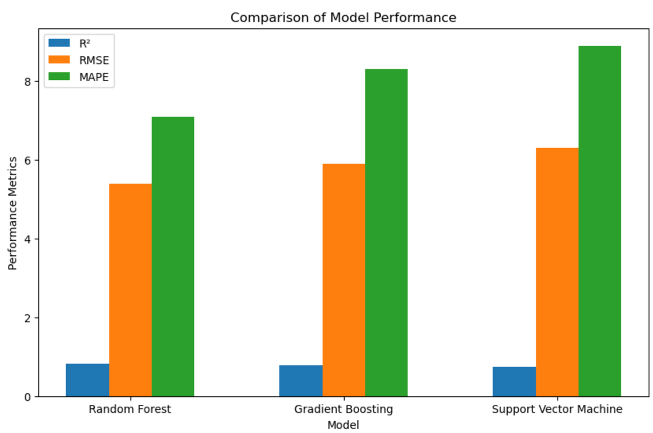

Figure 2: Comparison of Model Performance

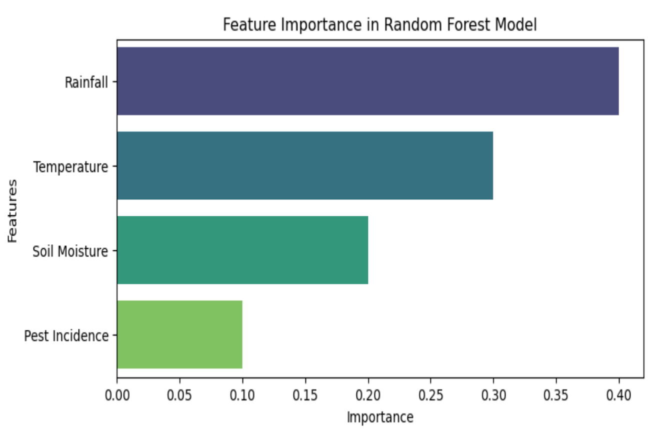

Figure 3: Feature Importance in Random Forest Model

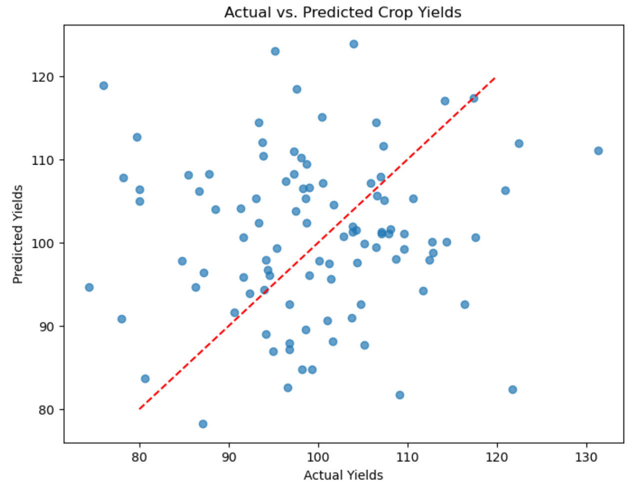

Figure 4: Actual versus predicted crop yield

Additionally, the data indicated the presence of the lowest error metrics, with a Root Mean Square Error (RMSE) of 5.4 and a Mean Absolute Percentage Error (MAPE) of just 7.1%. Nevertheless, the astonishing performance could mainly be attributed to the Random Forest's capacity to handle intricate interrelations, which is rather pivotal, particularly, as the variability and the nonlinearity of the climatic conditions are critical for the crop yield development.

Figure 3 shows the results of the Random Forest model feature importance, which indicates that the most significant factor was rainfall, then the temperature and, finally, the soil moisture, as highlighted. The acquired insight can help inform a number of effective strategies for both agricultural planning and resource allocation, which in the end can foster societal well-being. Also, the scatter plots presented in Figure 4 indicate that the actual yield was in a close knit with the yield forecasted by the model, confirming that the Random Forest regression was indeed accurate. Successful prediction of the yields would parallel a perfect prediction line, which can reinforce the belief in the model's accuracy. Such knowledge is indicative of a more practical scope for the model, giving farmers and policymakers handy tools that guarantee food security when the prevailing climatic conditions change.

Machine learning as the driving force behind the dramatic advances in crop yield prediction as shown in the study results has the potential to identify and debate complex processes. The Random Forest machine was a powerful example of predicting nineteen crops, which was mainly

possible owing to its capacity to bring in a variety of information. The key issues of environmental and climatic factors were addressed through the introduction of Model 0, which facilitated the harvesting of yield potential from all available crop scenarios, thus empowering agriculture stakeholders with timely information for appropriate product control decisions.
However, there are also issues needing to be tackled despite these improvements. Unpredictable conditions can be the cause of the differences in the quality of the data collected, hence, impairing the model's ability to make accurate predictions. Therefore, by developing research systems that benefit from the strengths of both traditional models and machine learning techniques so as to increase precision and practicality, these problems should be resolved.
The socio-technical change that is going to be realized through the use of machine learning is going to enable small/resource-poor farmers to gain access to high-quality agricultural inputs. The impact of this change is expected to be so profound that it is predicted that agro-technologies will be able to tackle climate change problems.

5. CONCLUSION

In conclusion, the combination of artificial intelligence, especially through machine learning models such as Random Forest, provides significant promise in the area of crop yield predictions, despite the obstacles introduced by climate change. The significance of our research lies in the fact that we acknowledged the ability of these models to process complex datasets and yield scenarios, thus assisting farmers and policymakers through informed decision-making. Despite the models' high precision, various data and regional differences must be addressed, and the traditional agricultural practices must be integrated. The ongoing improvement and the accessibility of these technologies can help rural farmers and part of the overcoming of challenges that are resistant to climate change.

REFERENCES

[1] G. KAÇMAZ AKKURT, "Vulnerability to Climate Change," in *Sustainability, Conservation and Ecology in Spatial Planning and Design: New approaches, solutions, applications*, 2023. doi: 10.4018/978-1-5225-0803-8.ch066.

[2] P. Choudhary, P. Shukla, and M. Muthamilarasan, "Genetic enhancement of climate-resilient traits in small millets: A review," 2023. doi: 10.1016/j.heliyon.2023.e14502.

[3] Y. Guo *et al.*, "Integrated phenology and climate in rice yields prediction using machine learning methods," *Ecol Indic*, vol. 120, 2021, doi: 10.1016/j.ecolind.2020.106935.

[4] P. U. Patil, S. B. Lande, V. J. Nagalkar, S. B. Nikam, and G. C. Wakchaure, "Grading and sorting technique of dragon fruits using machine learning algorithms," 2021. doi: 10.1016/j.jafr.2021.100118.

[5] L. S. Cedric *et al.*, "Crops yield prediction based on machine learning models: Case of West African countries," 2022. doi: 10.1016/j.atech.2022.100049.

[6] T. Hasegawa *et al.*, "A global dataset for the projected impacts of climate change on four major crops," *Sci Data*, vol. 9, no. 1, 2022, doi: 10.1038/s41597-022-01150-7.

[7] H. Pallathadka, M. Mustafa, D. T. Sanchez, G. Sekhar Sajja, S. Gour, and M. Naved, "IMPACT OF MACHINE learning ON Management, healthcare AND AGRICULTURE," *Mater Today Proc*, vol. 80, 2023, doi: 10.1016/j.matpr.2021.07.042.

[8] H. Pallathadka, M. Jawarneh, F. Sammy, V. Garchar, T. Sanchez, and M. Naved, "A Review of Using Artificial Intelligence and Machine Learning in Food and Agriculture Industry," in *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering, ICACITE 2022*, 2022. doi: 10.1109/ICACITE53722.2022.9823427.

[9] T. Hu *et al.*, "Crop yield prediction via explainable AI and interpretable machine learning: Dangers of black box models for evaluating climate change impacts on crop yield," *Agric For Meteorol*, vol. 336, 2023, doi: 10.1016/j.agrformet.2023.109458.

[10] M. Kuradusenge *et al.*, "Crop Yield Prediction Using Machine Learning Models: Case of Irish Potato and Maize," *Agriculture (Switzerland)*, vol. 13, no. 1, 2023, doi: 10.3390/agriculture13010225.

[11] A. Belhadi, S. S. Kamble, V. Mani, I. Benkhati, and F. E. Touriki, “An ensemble machine learning approach for forecasting credit risk of agricultural SMEs’ investments in agriculture 4.0 through supply chain finance,” *Ann Oper Res*, 2021, doi: 10.1007/s10479-021-04366-9.

[12] Shruti *et al.*, “Developing an NIRS Prediction Model for Oil, Protein, Amino Acids and Fatty Acids in Amaranth and Buckwheat,” *Agriculture (Switzerland)*, vol. 13, no. 2, 2023, doi: 10.3390/agriculture13020469.

[13] Anshul and R. Singh, “Crop Yield Prediction and Climate Change Impact Assessment Using Machine Learning Technology in Agriculture,” in *Lecture Notes in Networks and Systems*, 2023. doi: 10.1007/978-981-19-9304-6_33.

[14] R. Z. Abramoff, P. Ciais, P. Zhu, T. Hasegawa, H. Wakatsuki, and D. Makowski, “Adaptation Strategies Strongly Reduce the Future Impacts of Climate Change on Simulated Crop Yields,” *Earths Future*, vol. 11, no. 4, 2023, doi: 10.1029/2022EF003190.

[15] M. Gomathy and K. Kalaiselvi, “Climate change and its impact on agriculture,” in *Advanced Technologies for Smart Agriculture*, 2023. doi: 10.55126/ijzab.2024.v09.i04.004.

[16] K. Jhajharia and P. Mathur, “A comprehensive review on machine learning in agriculture domain,” 2022. doi: 10.11591/ijai.v11.i2.pp753-763.

[17] G. Leng and J. W. Hall, “Predicting spatial and temporal variability in crop yields: An inter-comparison of machine learning, regression and process-based models,” *Environmental Research Letters*, vol. 15, no. 4, 2020, doi: 10.1088/1748-9326/ab7b24.

[18] B. S. Sidhu, Z. Mehrabi, N. Ramankutty, and M. Kandlikar, “How can machine learning help in understanding the impact of climate change on crop yields?,” *Environmental Research Letters*, vol. 18, no. 2, 2023, doi: 10.1088/1748-9326/acb164.

[19] A. Crane-Droesch, “Machine learning methods for crop yield prediction and climate change impact assessment in agriculture,” *Environmental Research Letters*, vol. 13, no. 11, 2018, doi: 10.1088/1748-9326/aae159.

[20] A. B. Sarr and B. Sultan, “Predicting crop yields in Senegal using machine learning methods,” *International Journal of Climatology*, vol. 43, no. 4, 2023, doi: 10.1002/joc.7947.

[21] L. Li *et al.*, “Integrating machine learning and environmental variables to constrain uncertainty in crop yield change projections under climate change,” *European Journal of Agronomy*, vol. 149, 2023, doi: 10.1016/j.eja.2023.126917.

[22] R. Aworka *et al.*, “Agricultural decision system based on advanced machine learning models for yield prediction: Case of East African countries,” *Smart Agricultural Technology*, vol. 2, 2022, doi: 10.1016/j.atech.2022.100048.

[23] Kaggle, “Crop Yield Prediction Dataset.”