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To Analysis the Impact of Climate Change on Production Using Machine Learning

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Abstract

Agricultural production relies heavily on weather conditions, which are intricately linked to each other. Climate change plays a crucial role in causing biotic and abiotic stresses on plants, resulting in a detrimental impact on global agriculture. This paper aims to assess the influence of climate change, specifically the impacts of rainfall and temperature, on production. In this study, a CNN-LSTM machine learning model is utilized to investigate the impact of climate change on production. Climate change is a worldwide phenomenon that presents significant challenges across various sectors, including agriculture, manufacturing, and energy production. The aim of this research is to evaluate the effects of climate change on production efficiency, resource allocation, and overall performance.

Keywords: *Agricultural production, Climate change, machine learning, rainfall, temperature, CNN-LSTM.*

1. Introduction

Climate change presents urgent global concerns and imposes substantial obstacles across diverse sectors, including agriculture, energy, and manufacturing. Understanding and quantifying the impact of climate change on production systems is crucial for designing effective mitigation and adaptation strategies. Recent advances in machine learning have provided important tools for analyzing complex information and gaining significant insights. These findings are critical for comprehending the complex links between climate change and production outcomes **(Singh et al., 2023)**. Climate change is one of the most urgent worldwide environmental issues, with its consequences predicted to persist and worsen in the next decades **(Zhang et al., 2020)**.

One of the most significant issues facing humanity now is climate change **(Farajzadeh et al., 2022)**. Recent decades have seen a number of natural disasters brought on by climate change, including extreme weather, unforeseen temperature changes, and variations in rainfall. As a result, there is a greater knowledge of and commitment to combating climate change **(Ojo and Baiyegunhi, 2021)**. Agriculture productivity is significantly impacted by climate change, which also increases the risk of famine and food insecurity. The latter is a significant problem in regions that frequently experience droughts or other natural disasters. Climate elements that affect crop yield include rainfall, air temperature, humidity, and solar radiation. Multiple research studies have consistently demonstrated that crop yields and food security are influenced by various global and regional climate indicators **(Javadinejad et al., 2021)**.

Global industrialization will increase greenhouse gas (GHG) emissions, lead to a rise in global temperatures, and have an adverse impact on the environment. The majority of nations intend to reach carbon neutrality by 2050–2070, while just 4.5% of nations have already done so **(Chen et al., 2022)**. Due to the overuse of fossil fuels, the shipping industry also contributes to GHG emissions. In 2018, the shipping industry produced roughly one billion metric tons of CO2 equivalents of greenhouse gas emissions, or about 3% of all anthropogenic emissions worldwide **(Watanabe et al., 2022)**.

Climate change is an ongoing phenomenon, not merely a future occurrence. It has now been indisputably established as a reality, presenting humanity with its greatest challenge. Consequently, addressing climate change has become the most urgent concern of our time. The global average temperature has unmistakably risen by 0.30-

0.60 °C over the past century, while the sea level has experienced a rise of 10-20 cm during the same period, attributed to an evolving and vulnerable climate **(Rahman et al., 2020)**.

1.1 Climate Change and Its Impacts:

Changes in weather patterns, including variations in temperature, precipitation, and the occurrence of extreme events, characterize climate change. These changes are the result of human activities, specifically the emission of greenhouse gases. These changes have far-reaching consequences for various sectors, including agriculture, where altered growing conditions, increased pest pressures, and changes in water availability can affect crop yields and food security. Similarly, climate change affects energy production, as changing weather patterns influence renewable energy generation and the performance of traditional power plants. Understanding the multifaceted impacts of climate change on different production systems is essential for devising strategies to mitigate risks and adapt to new conditions **(Kumar et al., 2020)**.

The viewpoints that are explicit and revocable can be used to arrange the effects of elevation change. Because of the global temperature rise, some overall impacts can be encouraged, such as less severe winters and more vegetation in high altitude regions. However, compared to the superior effects, the antagonistic (negative) effects clearly come out on top. Some of the negative consequences brought on by elevation change, particularly when combined with sanctifying through water and an Asian aesthetic, can be structured as follows. Some causes are listed below:

- Global warming has an impact on nature.
- Pollution and excessive use of electronic devices like air conditioners and refrigerators.
- The majority of scientific experiments include nuclear power.
- Lake pollution is one of the primary causes of sea pollution.
- The indiscriminate use of fuel on a global scale.
- There is a rapid melting of the glaciers and this is the primary reason why the water level rose.

1.2 Factors Affecting the Crop Production

There are several factors which affect the production of agriculture very highly.

- **Variation of Crop Yield with Rainfall:** A key element in the production of agriculture is rainfall. Rainfall variations may have an impact on crop productivity. A high rainfall rate may contribute to low productivity. There shouldn't be too much rain. The optimal rainfall range is between 300 and 600 millimeters, which may result in exceptionally high or ordinary output.
- **Variation of Humidity Factor:** The metrological qualities have a considerable impact on the production of agricultural items. Humidity is one of the most important metrological characteristic components. Any crop will grow more effectively in humid conditions.

2. Literature Review

Singh et al. (2023) investigated the association between weather and agricultural production. They discovered a clear link between these two elements, with climate change emerging as a major cause of both biotic and abiotic pressures on plants. These stressors, in turn, have a negative impact on world agricultural output. Climate change has an effect on agricultural land in a number of ways, including periodic variations in temperatures and rainfall, weed changes, microbiological activity, heat waves, and changes in the quantity of CO2 or ozone in the atmosphere. Since the warnings about climate change are having negative effects on agricultural production and are negotiating the system of global food security, the study's focus has been heavily drawn to these issues. Machine learning (ML) is one of the new techniques that have been developed as a result of the challenges associated with extracting information from unstructured datasets. ML may be efficiently used to integrate information with agricultural yield estimation.

Shams, Mahmoud Y., et al. (2023) investigated a Model Based on Machine Learning to Predict Temperature Under Climate Change Effects, emphasizing the significance of climate change forecasting. They forecast temperature using ten features, including year, month, and atmospheric components, using machine learning (ML). Over the past century, global temperatures have risen, causing rising sea levels and more catastrophic weather occurrences. SVM, K-Nearest Neighbour, Random Forest, Decision Tree, Linear Regression, and Cat Boost Regressor were among the ML regression models used in this work to investigate the relationship between average world temperature and other parameters. The Cat Boost Regressor demonstrated the best performance among the models evaluated, with MAE, RMSE, MSE, and R^2 values of 0.0036, 0.054, 0.003, and 92.40%, respectively.

Hasegawa et al. (2022) explored the importance of accurate estimations of the Impacts of changing the climate on crop production in determining the sustainability of food systems. On a regional, global, and site-specific scale, crop simulation studies have been carried out for nearly 40 years, and they have been critical data sources for analyzing the implications of climate change. However, the vast amount of data that this research produced has not been made accessible to the general public. Here, they establish a worldwide dataset by combining information from previously published meta-analyses with details discovered from a recent literature search that includes current crop models. The new worldwide dataset is based on 8703 simulations from 202 studies released between 1984 and 2020. In addition to the foregoing, this report contains information on geographical regions, current temperatures, precipitation levels, predicted temperature and precipitation changes, and the influence on four important crop yields in 91 nations. This extensive dataset is a great resource for enhancing data-centric machine learning algorithms and provides a solid foundation for quantitatively studying the influence of climate change on food output in the twenty-first century.

Habib-ur-Rahman et al. (2022) examined how climate change threatens food-insecure agricultural production, notably in Asia. The study found that drought, heat waves, unpredictable rainfall, storms, floods, and new insect pests hurt farmers' livelihoods. Climate projections suggest a high temperature increase, variable rainfall patterns with rising intensity, and variability in extreme event climatic trends. The authors conducted a case study to examine climate change's impact and design mid-century (2040-2069) adaptation strategies for rice and wheat crops, vital for food production. Climate change scenarios anticipated 14.1% to 17.2% rice and wheat yield losses. The report recommends climate-smart and resilient agriculture for productivity. It reviews the literature on climate change's negative effects on agricultural productivity, highlighting Asia's major issues and sustainable agriculture possibilities. Addressing agricultural challenges and opportunities has several options. These include Legume-based crop rotation, mixed livestock systems, agroforestry, climate-resilient plant and animal varieties, decision support systems, and early warning systems, smart technologies for climate, carbon sequestration, energy, water, and soil management, and biodiversity enhancement. These methods can reduce climate change, increase agricultural productivity, and guarantee food security.

Haq et al. (2022) analyzed environmental parameters using AI and ML. This study uses the Long Short Term Memory model to forecast major environmental factors using a deep neural network. Hydrological models and forest expansion predictions require correct snow cover and NDVI predictions. Due to its adaptive processing, time series forecasting uses artificial neural networks (ANN), such as LSTM and RNN. LSTM RNNs can detect long-term dependencies. The authors use a coarse-to-fine approach, examining relevant studies and using LSTM analysis on a Himachal Pradesh dataset. The dataset includes 2001–2017 temperature, snow cover, and vegetation index data. The study found that the suggested system's tools and approaches speed up environmental factor assessment, adjustment, and improvement.

Kandasammy et al. (2022) conducted a study to investigate the connection between climate variability and the substantial variation in precipitation and dry land cultivation. The objective was to assess the susceptibility of dry land producers to climate change and aid in their adaptation. Understanding the influential factors in emerging nations is essential for local policy research. This study employed the Vulnerability index and Machine Learning techniques to assess the vulnerability levels and factors impacting the dry land population in Southern India. The ML analysis revealed that "engagement in awareness campaigns, food income sources, farm size, and education level of dry land farmers" were significant determinants of community vulnerability. Effectively reducing the vulnerability of dry land producers by identifying coping strategies. The findings of this study suggest the need for future research and policy development in order to assure the micro-level sustainability of dry land producers in the face of climate change.

Crane et al. (2018) utilized machine learning to estimate crop yields and assess the impact of climate change. To predict climate change's effects on agriculture, the author emphasizes crop yields' weather dependence. The article introduces a semi parametric deep neural network yield modeling method. The research shows the efficacy of this method for forecasting corn yields in years that were not included in the model training over conventional statistical techniques and fully nonparametric neural networks using data on Midwest maize yields. In high-dimensional datasets, this methodology accounts for complex nonlinear interactions, parametric structure, and undiscovered cross-sectional heterogeneity. The study also examines how climate change affects corn yield using climate model scenarios. Climate change reduces corn output, although less than classical statistical approaches predicted. In hottest places and scenarios, the proposed method appears less pessimistic.

Table 1: Comparison of Literature Review

Author and Year	**Method**	**Focus**	**Key Findings**
Singh et al. (2023)	Machine Learning (ML)	Impact of climate change on agricultural production	Changes in precipitation, temperature, weeds, microbiological activity, heat waves, CO_2 and ozone levels, and heat waves all have an impact on agricultural land as a result of climate change. The research focuses on the use of machine learning to integrate data for agricultural productivity estimation.
Shams et al. (2023)	Machine Learning (ML)	Predicting temperature under climate change effects	ML regression models were used to predict temperature based on ten features. The Cat Boost Regressor performed the best, with low errors and a determination coefficient of 92.40%. The study emphasizes the relevance of climate change forecasting and its impact on global temperatures and weather events.
Hasegawa et al. (2022)	Crop simulation and data analysis	Evaluating the Effects of Climate Change on Crop Yield	The study establishes a global dataset combining information from meta-analyses and recent literature searches. It includes data on temperature, precipitation, and crop yields in 91 countries under various emission scenarios. The dataset supports data-driven machine learning

			applications and provides insights into how climate change affects crop yield.
Habib-ur-Rahman et al. (2022)	Impact assessment and adaptation strategies	Climate change's threat to food-insecure agricultural production	The research investigates the detrimental impacts of climate change on agricultural productivity in Asia, focusing on rice and wheat crops. It projects yield losses and suggests adaptation strategies such as climate-smart agriculture, early warning systems, and biodiversity enhancement. The objectives are to reduce climate change, boost agricultural productivity, and guarantee food security.
Haq et al. (2022)	Artificial Neural Networks (LSTM)	Forecasting and analyzing environmental factors	The study utilizes LSTM models to forecast environmental factors such as temperature, snow cover, and vegetation index. The proposed system's tools and approaches accelerate the assessment, adjustment, and improvement of environmental factors.
Kandasammy et al. (2022)	Vulnerability assessment and Machine Learning (ML)	Assessing vulnerability and factors affecting dryland farmers	ML techniques were employed to assess the vulnerability of dryland farmers in Southern India. Factors such as awareness campaigns, food income sources, farm size, and education level were found to influence vulnerability. The study highlights the importance of identifying coping strategies and suggests further research and policy development for the sustainability of

			dryland farmers in a changing climate.
Crane et al. (2018)	Deep Neural Network Yield Modeling	Crop yield prediction and climate change impact assessment	The paper introduces a semi-parametric deep neural network method for predicting crop yields and assessing climate change impacts. The method outperforms classical statistical approaches and shows that climate change reduces corn yield, although less pessimistically than predicted by classical methods.

3. Research Methodology

This innovative research strategy uses a novel machine learning approach to analyze the effects of climate change on production in depth, leading to more accurate and insightful results. The methodology centers on a modified CNN-LSTM model, which combines the strengths of both CNN and LSTM to enhance the analysis process. By leveraging this advanced ML technique, researchers are able to comprehensively examine how climate change influences various aspects of production, such as crop yields, industrial output, and natural resource availability. The utilization of the CNN-LSTM model enables the identification of intricate patterns and relationships within vast datasets, allowing for a deeper understanding of the complex interplay between climate change and production.

Machine Learning Models

Multiple research studies have substantiated the significance of machine learning as an essential tool for analyzing the impact of climate change. Machine learning, as a technology, plays a vital role in assisting farmers in minimizing agricultural losses by providing them with comprehensive crop guidance and valuable insights. In this particular study, modified CNN-LSTM model, was investigated. The selection of this approach was based on the quantitative nature of the predictions and the scale of the dataset, prioritizing numeric variables over categorical ones.

CNN-LSTM: The paper proposed a CNN-LSTM network based on CNN and RNN's achievements. CNN can infer numerous details from a picture like the human brain. An LSTM may bridge significant input latencies across any time span. LSTM improves the analysis of crop growing cycles of varying durations by presenting temporal patterns at different frequencies.

In addition to analyzing performance parameters such as accuracy, specificity, F1-score, and support measure value, and this revised CNN-LSTM model would be utilized to make predictions about crop records.

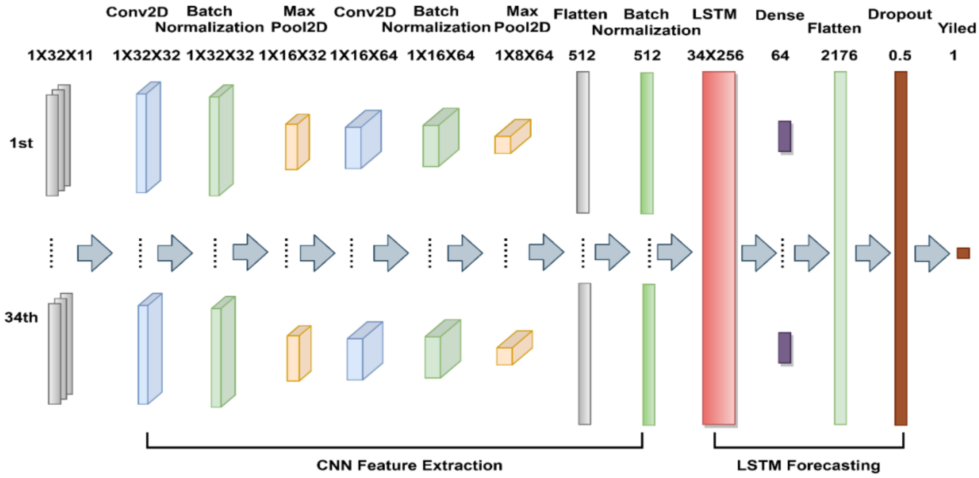

Fig 1: The architecture of the proposed CNN-LSTM model.

Result & Discussion

Climate-based agricultural production

Agricultural production occurs through a cyclical process, where considerations are made for climate change and the planting of crops. This production process aligns with distinct seasons, namely the monsoon, winter, and summer crop production systems. As a result, agricultural production adapts and recycles in accordance with weather patterns. However, climate change poses a significant threat to agricultural output. The reliance on the monsoon for successful cultivation makes agriculture vulnerable to the impacts of climate change. The consequences of this shift can be witnessed in the form of reduced soil productivity caused by climate change. For instance, elevated temperatures during summer can lead to food shortages and flooding during the rainy season.

Table-2 Temperature and Rainfall

Years	**Temperature (+increase,-Decrease) in °C**	**Rainfall (+increase,-Decrease)**
2010-2011	+ 0.7 °C	-120
2011-2012	+ 0.6 °C	-80
2012-2013	+ 0.7 °C	-150
2013-2014	+ 0.7 °C	-180
2014-2015	+ 0.6 °C	-220
2015-2016	+ 0.5 °C	-70
2016-2017	+ 0.5 °C	-200
2017-2018	+ 0.9 °C	-120
2018-2019	+ 0.5 °C	-170
2019-2020	+ 0.4 °C	+50

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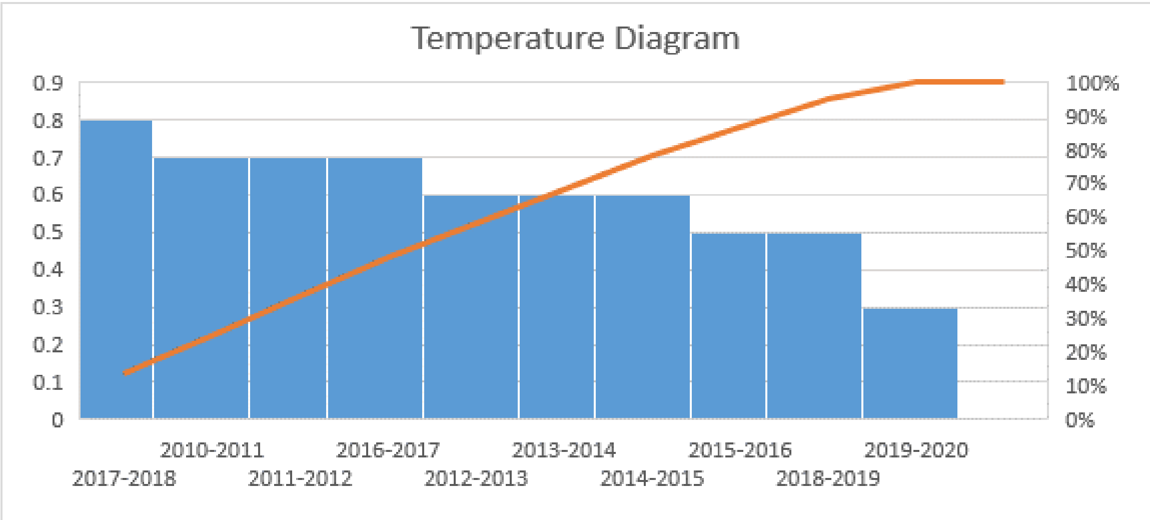

Fig 2: comparative temperatures over a span of ten years

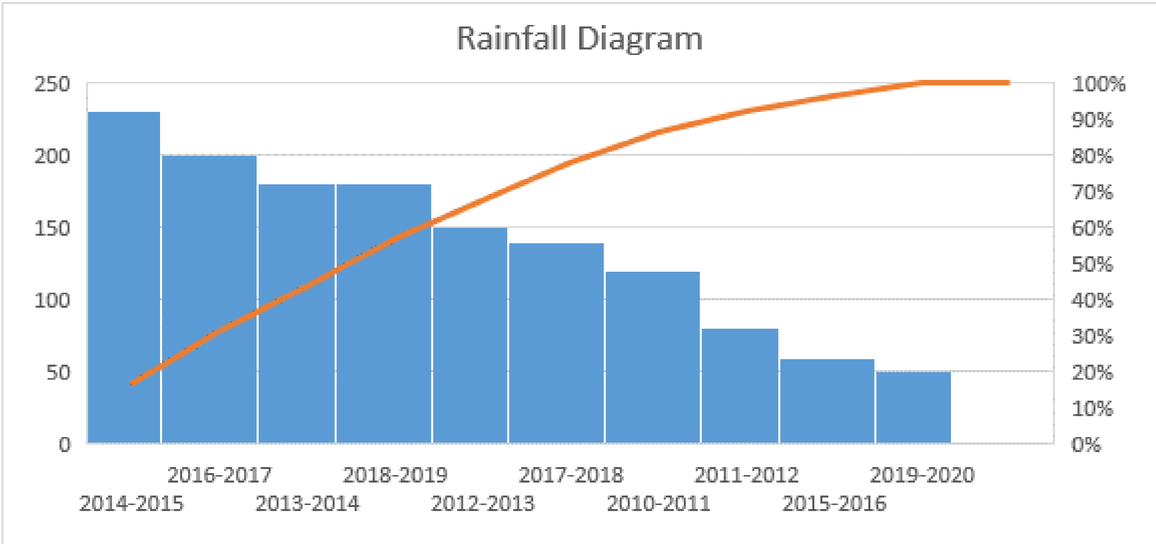

Fig 3: comparative rainfall data over a span of ten years

The first diagram depicts the comparative temperatures over a span of ten years, indicating which years experienced higher or lower temperatures in relation to each other. The most significant temperature increase observed between 2010 and 2020 amounted to 0.70 degrees Celsius. The rise in temperature can be attributed primarily to the devastating impact of deforestation and the destruction of arable lands. Consequently, the overall temperature continues to rise steadily. Another contributing factor to this phenomenon is the decrease in rainfall patterns. The second diagram (Fig 3), focusing on rainfall data, showcases the years with the lowest precipitation levels in the past decade. Notably, the highest recorded rainfall in 2014-2015 exceeded the average by 800 mm.

Conclusion

This study utilized machine learning techniques, specifically the CNN-LSTM model, to analyze the impact of climate change on agricultural production. The findings highlight the significant challenges posed by climate change, such as altered weather patterns, increased biotic and abiotic stresses on plants, and changes in water availability. These factors have detrimental effects on crop yields, food security, and overall production efficiency. The research demonstrated that temperature, and rainfall are crucial factors affecting agricultural productivity, with temperature rising and precipitation fluctuating over a ten-year period. These changes disrupt planting seasons, reduce soil productivity, and contribute to food shortages and flooding. By utilizing the CNN-LSTM model, the study provided a comprehensive understanding of how climate change affects production outcomes, highlighting the need to address climate change and develop effective strategies for adaptation and mitigation. Leveraging machine learning and advanced analytics can deepen our understanding of climate change's complex impacts and facilitate informed decisions for sustainable and resilient agricultural systems.

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