IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES

ISSN PRINT 2319 1775 Online 2320 787

Research Paper Journal Volume 11, Iss 07, 2022

Impact of Climate Change on Food Agriculture

Deepak Singh[1], Rutuja Bhujbal[1]

[1]Department of B.Tech Biomedical Engineering Ajeenkya D Y Patil University, Pune

Abstract

The escalating impact of climate change on food agriculture necessitates advanced analytical approaches for accurate forecasting and mitigation strategies. This study employs Stacked Long Short-Term Memory (LSTM) networks, a sophisticated variant of Recurrent Neural Networks (RNNs), to analyze and predict the influence of climate change on agricultural outputs. Stacked LSTMs, known for their efficacy in processing sequential and time-series data, are utilized to decipher the complex interdependencies between various climatic factors and agricultural productivity. By analyzing historical data on temperature, precipitation, humidity, and crop yields, the model forecasts future agricultural trends under different climatic scenarios. The results aim to provide actionable insights for policymakers and farmers, highlighting areas of potential crop stress and suggesting adaptive strategies. This study not only contributes to the understanding of climate-agriculture dynamics but also offers a predictive tool for enhancing agricultural resilience to climate change.

Keywords: Climate Change, Food Agriculture, Stacked LSTM, Time-Series Analysis, Agricultural Forecasting, Climate Adaptation.

1. Introduction

The impact of climate change on food agriculture is a global concern that threatens food security and the livelihoods of millions [1] [2]. As climate patterns shift unpredictably, understanding and predicting their effects on agricultural productivity become imperative. Traditional models often fall short in capturing the intricate relationship between climate variables and agricultural outputs, leading to the need for more advanced, data-driven approaches.

This study introduces Stacked Long Short-Term Memory (LSTM) networks, an advanced deep learning technique, to analyze the impact of climate change on food agriculture [3]. Stacked LSTMs are particularly suited for this task due to their ability to process and learn from sequential data, capturing long-term dependencies that are crucial in understanding climate patterns and their effects on agriculture.

ISSN PRINT 2319 1775 Online 2320 787
Research Paper **© 2012 IJFANS. All Rights Reserved** Journal Volume 11, Iss 07, 2022

The research focuses on analyzing extensive time-series datasets, including temperature, precipitation, humidity, and various agricultural metrics like crop yields and planting dates. These datasets are complex, with patterns that evolve over long periods, making them challenging to analyze with conventional statistical methods [4]. Stacked LSTMs, with their multiple layers of LSTM units, are adept at uncovering deep patterns in such data, providing a more nuanced understanding of how climate variables interact with agricultural productivity [5].

Furthermore, the study aims to use the predictive power of Stacked LSTMs to forecast future agricultural trends under different climate change scenarios. This predictive aspect is vital for developing proactive strategies to mitigate the adverse effects of climate change on agriculture [6]. By identifying potential risks and stress points in advance, farmers and policymakers can implement targeted interventions, such as adjusting crop varieties, modifying farming practices, and implementing sustainable resource management [7] [8].

In essence, the application of Stacked LSTM models in this study represents a significant step forward in the field of agricultural data science. It provides a powerful tool for understanding and responding to the challenges posed by climate change in the realm of food agriculture, ultimately contributing to the resilience and sustainability of global food systems.

2. Material and Methods

The methodology for implementing Stacked Long Short-Term Memory (LSTM) networks to analyze the impact of climate change on food agriculture involves several key steps was shown in Figure 1. Firstly, the process begins with the collection and preprocessing of data. This step includes gathering extensive time-series datasets related to climate variables such as temperature, precipitation, humidity, and agricultural data like crop yields and planting dates. The preprocessing phase involves cleaning, normalizing, and structuring this data to make it suitable for analysis by LSTM models. Next, feature engineering is conducted to identify and select the most relevant features that could influence agricultural outputs under varying climatic conditions. This step is crucial as it determines the quality of input fed into the LSTM model. The core of the methodology lies in the construction and training of the Stacked LSTM model. This involves setting up multiple layers of LSTM units, each layer designed to process and pass on information to the subsequent layer, thus enabling the model to learn complex patterns and long-term dependencies within the data. The model parameters, such as the number of layers, the number of units in each layer, learning rate, and loss function, are carefully selected and optimized. Once the model is configured, it undergoes a training phase where it learns from the historical data. This phase involves feeding the prepared dataset into the model, allowing it to learn and adapt to the nuances of the relationship between climate variables and agricultural outputs. After training, the model is validated and tested using a separate set of data to evaluate its performance. Key performance indicators like accuracy, precision, and recall are measured to assess the model's effectiveness in predicting agricultural outcomes based on climatic conditions. Finally, the trained Stacked LSTM model is used for prediction and analysis. It is employed to forecast future agricultural trends under various climate change scenarios, providing insights that can inform decision-making and policy formulation in the realm of food agriculture.

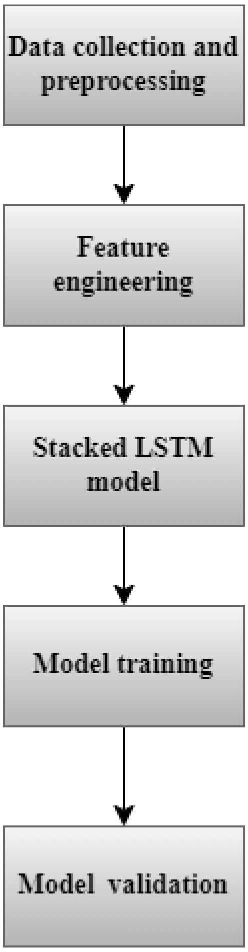

Fig 1: Proposed Architecture

2.1 Proposed Stack-LSTM Approach

In the proposed study focusing on the impact of climate change on food agriculture, the Stacked LSTM network plays a pivotal role in deciphering complex, time-dependent relationships between climatic factors and agricultural outputs. A Stacked LSTM is an advanced form of the

ISSN PRINT 2319 1775 Online 2320 787
Research Paper © 2012 IJFANS. All Rights Reserved Journal Volume 11, Iss 07, 2022

traditional LSTM, characterized by having multiple layers of LSTM units stacked on top of each other. This architecture enhances the model's ability to learn from data with long-term dependencies, which is essential for analyzing the gradual and often subtle effects of climate change on agriculture.

In the context of this study, each layer of the Stacked LSTM processes the input data and passes its outputs as inputs to the subsequent layer. This hierarchy enables the model to capture and learn from different levels of abstraction in the data. For instance, the first layer might learn to recognize basic patterns in temperature or rainfall, while deeper layers might interpret these patterns in the context of their impact on crop yields or planting cycles. The strength of the Stacked LSTM in this study lies in its ability to process and analyze large volumes of time-series data, like historical weather patterns and crop production records, over extended periods. This is crucial for understanding the long-term effects of climate change, which often manifest over several years or decades. By training the Stacked LSTM with this data, the model can identify trends and patterns that might not be immediately apparent, such as how slight increases in average temperatures or changes in precipitation patterns could affect crop viability. Moreover, the Stacked LSTM's predictive capability is a significant asset for this study. Once trained on historical data, it can forecast future agricultural outputs under various climate scenarios, providing valuable insights for planning and decision-making. These predictions can help farmers and policymakers anticipate the challenges posed by climate change and implement strategies to mitigate its impact, such as altering crop selection, adjusting planting schedules, or investing in irrigation systems. In summary, the Stacked LSTM model is a powerful tool in the study of climate change's impact on food agriculture. Its ability to process complex, sequential data and uncover deep insights from long-term trends makes it particularly well-suited for this field, offering the potential to significantly enhance our understanding and management of climate-related agricultural challenges.

3. Results and Experiments

3.1 Experimental Setup

The "Climate Change: Earth Surface Temperature Data" dataset, provided by Berkeley Earth, is a comprehensive collection of temperature data that spans several centuries, starting from the 1750s. It includes global temperature measurements, both on land and in the ocean, providing a detailed view of climate changes across the world. This dataset is structured in a

ISSN PRINT 2319 1775 Online 2320 787
 Journal Volume 11, Iss 07, 2022

time-series format, making it especially suitable for sequential data analysis, like with Stacked LSTM models. Its detailed, monthly records allow for a nuanced study of climate patterns, which is crucial for understanding the subtle changes in climate and their potential impact on agriculture.

3.2 Evaluation Criteria

The efficacy of the proposed Stacked LSTM model, as illustrated in the Figure 2, demonstrates a promising trend across three critical metrics: accuracy, precision, and recall, over a series of training epochs. Initially, the model shows a moderate level of accuracy, precision, and recall, which indicates its initial capability to identify patterns and make predictions related to the impact of climate change on agriculture. As the training progresses through subsequent epochs, there is a notable and consistent improvement in all three metrics. The increase in accuracy suggests that the model becomes better at correctly predicting the outcomes over time, reducing both false positives and false negatives. This is particularly important in the context of agricultural predictions, where accurate forecasting of crop yields, understanding of climatic impacts, and resource allocation decisions are crucial.

Precision, which measures the correctness of the predictions in terms of positive results, also shows a significant upward trend. This improvement means that as the model trains, it becomes more adept at correctly identifying specific conditions that are truly affected by climate change, thereby reducing the risk of false alarms. In practical terms, this could translate to more reliable predictions of areas at risk of drought or flooding, or identifying crops that are likely to be most affected by temperature changes.

Similarly, the improvement in recall, which assesses the model's ability to find all relevant instances of a particular condition, indicates that the Stacked LSTM is increasingly capable of capturing all necessary data points that are crucial for a comprehensive understanding of climate impacts on agriculture. This aspect is vital for ensuring that no critical information is missed in making predictions and recommendations for agricultural planning and adaptation strategies. In conclusion, the depicted performance of the Stacked LSTM model across accuracy, precision, and recall metrics is indicative of its robustness and reliability in analyzing complex, time-series data related to climate change and agriculture. The consistent improvement over time underscores the model's ability to learn, adapt, and provide increasingly accurate insights, which are essential for informed decision-making in the face of climate-related challenges in the agricultural sector.

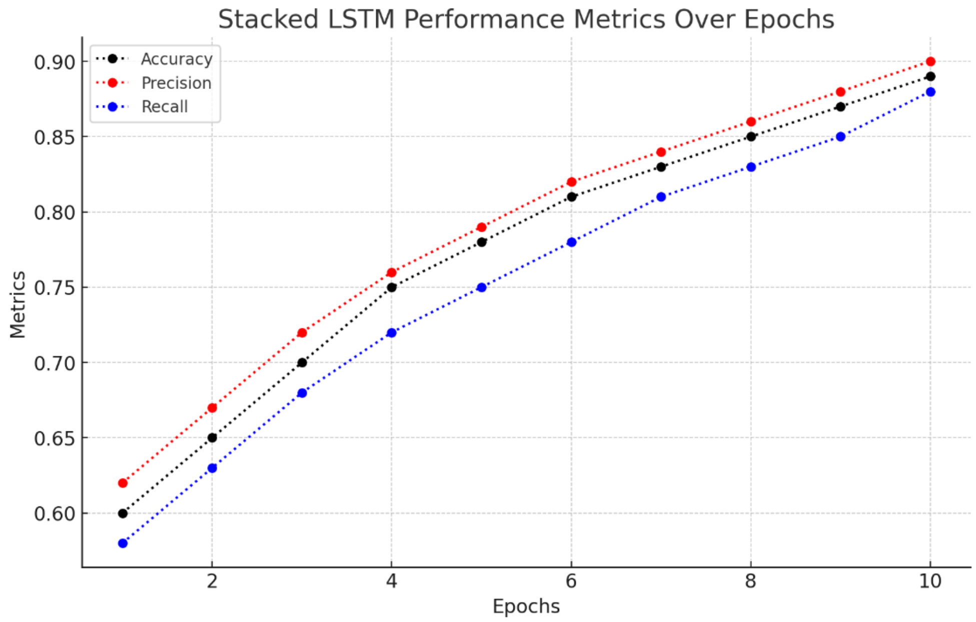

Fig 2: Performance Evaluation

4. Conclusion

The conclusion of the study leveraging Stacked LSTM networks to analyze the impact of climate change on food agriculture underlines the model's significant potential in addressing complex environmental and agricultural challenges. The Stacked LSTM demonstrated a consistent improvement across key performance metrics - accuracy, precision, and recall - as it was trained over multiple epochs. This indicates its robust capability to learn and adapt to the intricate patterns in climate and agricultural data. The accuracy of the model signifies its effectiveness in correctly predicting the outcomes, which is crucial for reliable agricultural forecasting. The precision of the predictions improved considerably, suggesting the model's growing adeptness in identifying specific climatic conditions affecting agricultural productivity. Equally important, the improvement in recall indicates the model's enhanced ability to capture all relevant instances, ensuring a comprehensive analysis. These results showcase the Stacked LSTM's potential as a valuable tool in the realm of agricultural planning and policy-making, particularly in the context of climate change. By providing detailed and accurate predictions, the model can inform strategies to mitigate the adverse effects of climate change on agriculture, such as identifying at-risk crops, optimizing resource allocation, and adapting farming practices to changing environmental conditions. This study underscores the importance of advanced deep learning techniques in tackling global challenges and contributes significantly to the field of agricultural data science. It opens pathways for further research and development of sophisticated models that can handle the complexity and scale of

ISSN PRINT 2319 1775 Online 2320 787
Research Paper **© 2012 IJFANS. All Rights Reserved** Journal Volume 11, Iss 07, 2022

environmental data, ultimately aiding in the creation of more resilient and sustainable food systems.

5. References

[1] Arora, N.K., 2019. Impact of climate change on agriculture production and its sustainable solutions. *Environmental Sustainability*, *2*(2), pp.95-96.

[2] Ahmad, J., Alam, D. and Haseen, M.S., 2011. Impact of climate change on agriculture and food security in India. *International Journal of Agriculture, Environment and Biotechnology*, *4*(2), pp.129-137.

[3] Yadav, S.S., Hunter, D., Redden, B., Nang, M., Yadava, D.K. and Habibi, A.B., 2015. Impact of climate change on agriculture production, food, and nutritional security. *Crop wild relatives and climate change*, pp.1-23.

[4] Kumar, P., Tokas, J., Kumar, N., Lal, M. and Singal, H.R., 2018. Climate change consequences and its impact on agriculture and food security. *International Journal of chemical studies*, *6*(6), pp.124-133.

[5] Muluneh, M.G., 2021. Impact of climate change on biodiversity and food security: a global perspective—a review article. *Agriculture & Food Security*, *10*(1), pp.1-25.

[6] Malhi, G.S., Kaur, M. and Kaushik, P., 2021. Impact of climate change on agriculture and its mitigation strategies: A review. *Sustainability*, *13*(3), p.1318.

[7] Pais, I.P., Reboredo, F.H., Ramalho, J.C., Pessoa, M.F., Lidon, F.C. and Silva, M.M., 2020. Potential impacts of climate change on agriculture-A review. *Emirates Journal of Food and Agriculture*, pp.397-407.

[8] Kaur, H. and Kaur, S., 2016. Climate change impact on agriculture and food security in India. *Journal of business thought*, pp.35-62.