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Impact of climate change on crop yield in Water Scare region through deep learning

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Abstract

Climate change poses a severe threat to agricultural sustainability, particularly in water-scarce regions such as Multan, Pakistan, which receives an annual average rainfall of only 186mm and experiences frequent drought conditions (Pakistan Meteorological Department, 2022). The increasing depletion of groundwater resources further exacerbates agricultural challenges in the region. It is a rising threat to agriculture, a fundamental component of food security worldwide, and due to this, new ways of formulating crop estimate models are needed. Most traditional approaches to forecasting ATTR might not accurately capture the complex and non-linear or even non-additive mechanisms that connect climate parameters and crop yields. In this work, we employ Long Short-Term Memory (LSTM networks) a state-of-art deep learning method to forecast crop yields based on temperature, rainfall, and crop production data. As a result, the LSTM model can process the sequential data and identify the temporal dependence pattern as the best model for this task. The main input data included climate and yield data from a particular year in a specific region and some preprocessing was done to handle missing values, scale inputs, and group rainfall data. The model had a MAPE of 5.36%, an MAE of 1136.70, and an RMSE of 1136.70 giving the model a prediction accuracy of 94.64%. This work shows the efficiency of the proposed model and confirms that this approach is more effective than traditional statistical methods. These predictions are highly accurate and provide valuable information for different users including farmers, policy-makers, and researchers. This work elucidates how LSTM-based models can help solve the future challenges of agricultural management and production. When able to yield reliable predictions of the yields, such models can also help in proper resource planning, managing the effects of climate change, and improving food security all over the world. As a result, it is evident that machine learning critically occupies the subject area in constructing a long-lasting agricultural future resistant to dramatic changes.

Keywords: Deep Learning; Long Short-Term Memory (LSTM); Crop Yield Prediction; Climate Change; Food Security analysis

1. Introduction

Multan, a key agricultural hub in Pakistan, is categorized as a semi-arid region with limited water availability for crop production. The city receives an average annual rainfall of 186mm, which is significantly lower than the minimum 500mm threshold required for sustainable rain-fed agriculture[1]. Additionally, erratic monsoon patterns and prolonged dry spells have intensified water stress, leading to declining groundwater levels and increased reliance on irrigation. According to the [2], Multan has experienced at least five drought years in the past two decades, further highlighting the vulnerability of its agricultural sector to climate variability. Agriculture has proved to be central to the growth of human societies as a means of producing food[3], providing a medium for exchange and, in fact, as the base upon which societies have depended for sustenance. Since the beginning of agriculture, people have used natural philosophies to dictate the climate and habits of the environment to know when and where to plant crops, when to tend to those plants, and when to harvest them[4]. Thanks to modern agriculture, technology has fitted the system of farming to be more productive. However, it is critical to distinguish between the tremendous growth of agricultural productivity and stability of harvests in recent decades and the basic fragility of agricultural production systems that hinges on the ability to adapt to environmental conditions[5], driven mainly by weather factors and changes in climate and season. These conditions have a great impact on the growth and yield of crops and their related farming criteria, which in turn have dynamic impacts on the farmer's economy, global food supply, and the sustainability of the environment.

The problem of forecasting regarding yields for crops is further complicated when factors like temperature and rainfall are factored into the mix within the climate system[6]. Weather conditions are a critical consideration within agriculture since a little shift in environmental conditions can trigger a massive difference in yields[3]. For example, unfavorable temperature levels may harm plants at certain development phases or irregular rainfall would cause either drought, which is destructive to crop production. In addition, the time of occurrence of rainfall and/or temperature changes is extremely significant to crops[7]; for instance, drought at critical development phases such as flowering or fruiting greatly reduces crop yield potential, while excess rainfall can either retard crop maturity or cause crop diseases.

The conventional yield prediction methods that mainly use historical records may not give a proper on more intricate interactions between climate and crops. This is where modern advancements in deep learning (DL) and artificial intelligence (AI)[8] Help, and become useful. In recent years, deep learning techniques, especially LSTM, have attracted a lot of attention in GWS due to massive data inputs and other hidden patterns that cannot be seen easily by even an analyst. Of these techniques, LSTM[9] Which is a specific type of RNN that has developed into a powerful tool for time series prediction. Problems where the sequence of data points is critical include the use of LSTMs in weather prediction and in determining agricultural yield[5].

The notion of applying deep learning techniques, LSTMs in this case, to attempt to forecast crop yields based on historical climate data is unique and timely in light of climate change. And so, with global temperatures continuing to climb and weather[9]. Becoming more unpredictable, it remains a concern as to how farmers can continue relying only on traditional methods of forecasting. AI and deep learning could play significant roles in the betterment and improvement of agricultural forecasting systems[10] and assist farmers in overcoming these challenges since it would help them make precise decisions regarding resources and management in a way that enhances the qualities of crops that would help them withstand the change in climate conditions[4]. This paper investigates the ability of LSTM networks[9] in predicting crop production based on temperature, rainfall, and crop production data from past seasons. Based on this data, we want to answer the question of whether an LSTM model[9] provides better and more accurate predictions than basic forecasting, which is valuable for farmers, decision-makers, and researchers.

The purpose of this research is to develop a forecasting model that incorporates past temperature and rainfall data over several years, as well as crop production data, to predict future crop production.[5]. This model could assist farmers in establishing a better way of predicting crop yields for the next season in case of bad planting seasons, making good planning right from planting seasons, especially concerning the use of water and fertilizers during planting for increased crop yields[4], and also assist farmers' crop selection as well as market segmentation and strategies. Furthermore, such a model could be used for more precise yield prediction, which would decrease food waste and increase overall food security, making the agricultural industry more sustainable[4].

This research is a small step, but a noteworthy one, in an attempt to reinvent the prediction of agriculture-related factors with machine learning systems[4]. The findings of this study also focus on improving the predictions of crop yields to advance the intelligent management of farming activities, as they contribute to food security under climate change[11]. In conclusion, this work aims to show how incorporating such sophisticated machine learning models like LSTMs with conventional techniques in agriculture can help improve the current agricultural system for the challenges of the 21st century[10]. It is difficult to overemphasize the importance of agriculture[12], as this sector has always been the foundation of human development, meeting the most basic human needs, such as food, materials for clothing, and job opportunities for billions of people globally[13]. It has always been the traditional way of producing food where farmers till the soil based on cycles, rainfall, and climatic conditions in a given region. Even with the developments in technology and efficiency in planting and dealing with crops, climatic changes remain one of the biggest challenges for farmers[14]. Since climate can significantly impact crop yields and production, fluctuations in temperature, rainy season, or occurrence of natural disasters such as droughts, floods, and storms pose a significant risk towards food insecurity, financial loss, and social unrest[9].

Deep learning (DL) and artificial intelligence (AI) [8] In the recent past, they have been considered to be very promising technologies that might be useful in altering how agricultural results are predicted and handled among the many DL methodologies. Deep learning algorithms [15] particularly the LSTM networks have been reported to offer remarkable performance in time series prediction. As opposed to non-recurrent machine learning models, LSTM is designed to handle sequential data in which the arrangement of the numbers matters. This makes them particularly useful when the data we are trying to predict, in this case, weather patterns and crop yields, tend to have temporal dependencies. These models can learn from the past to predict the future, which makes them very useful when it comes to trying to predict how much yield it will be possible to get from the next crop season, depending on the temperature, rainfall, and crop production[4] That has been recorded in the past. Many papers have been written regarding the application of machine learning for yield prediction for crops. Weather observation, soil type, and prior year production data have been used with regression models, S-V machines, and decision trees to predict crop yields[4]. Recently introduced deep learning architectures, such as LSTM networks, are preferred owing to the ability of the models to capture long-term sequences in sequential data processing. Earlier studies have shown that LSTM models can provide consistent estimates of crop yields[3], where weather patterns show temporal dependencies. Nevertheless, there is a research gap in the application of both temperature and rainfall data, besides crop yield data, for training LSTM models[9].

This study explores the potential of LSTM networks in predicting wheat yield based on temperature, rainfall, and production history in Multan, Pakistan. Wheat was selected because it is the most cultivated crop in the region, contributing significantly to Pakistan's food security and economy. Given the increasing climate variability, accurately forecasting wheat yield can help farmers and policymakers make informed decisions regarding irrigation, fertilization, and resource allocation[8].

2. Methodology

2.1 The Study Area

This research is focused on Multan, which is an agricultural area in Punjab, Pakistan that flattens productive fields and contributes approximately one of the largest portions of the agricultural production of the country. Multan, situated on the left bank of the Chenab River, is known for its hot semi-arid climate; scorching summer, moderate winter, and average annual rainfall is about 186mm, with the monsoon season having occasional rainfall. Multan has always been considered the agricultural hub of Pakistan, producing basic food crops like wheat, cotton, and sugarcane, especially in the world-renowned mango production areas. As with other areas of the country, Multan has also been the victim of a changing climate, concerning variation in temperature and rainfall. The uniqueness of these conditions, being climate sensitive, makes Multan important since, through the study that shall be conducted on the available data concerning weather conditions and the yield of crops, it will be established how to make the agricultural resources stronger and the resource management systems more effective in the region.

2.2 Data Collection and Preprocessing

Thus, the source of information for the study was three data sets that gave an overall account of climatic and agricultural patterns in the Multan region with special reference to yield. Mean maximum and minimum temperature information was obtained annually from the years 2007 to 2022. These indicators were chosen because they have a critical function in the growing cycles of crops, including flowering, fruit formation, and crop yield.

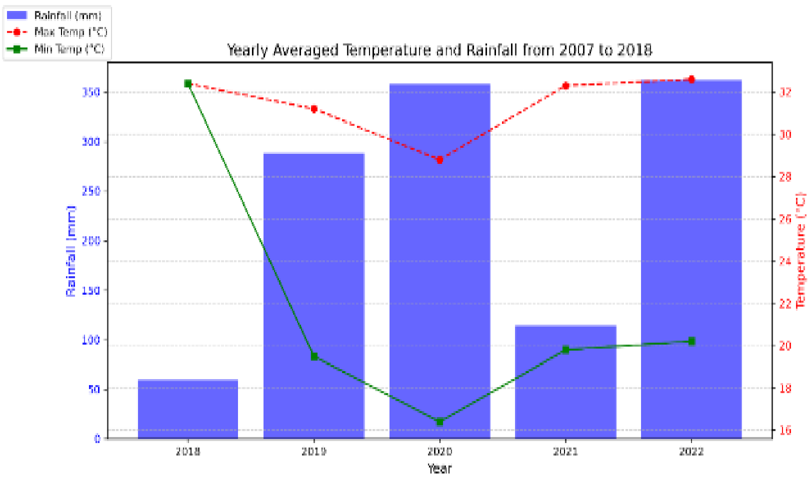

Fig. 1: Yearly averaged temperature and rainfall from 2007 to 2018

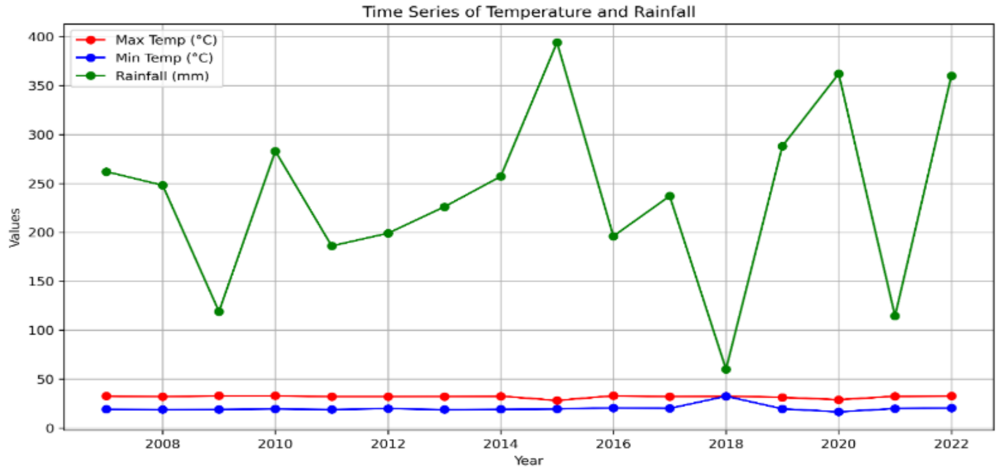

Fig. 2: Time series temperature and rainfall from 2007 to 2018

Rainfall data was categorized into two types: rainfall data from 2007 to 2022 including mean annual rainfall, which was used for comparing the overall availability of water for agricultural activities, and monthly rainfall data from 2018 to 2022. The monthly data proved especially useful in determining how rainfall or its absence made its biggest impact within the crop season.

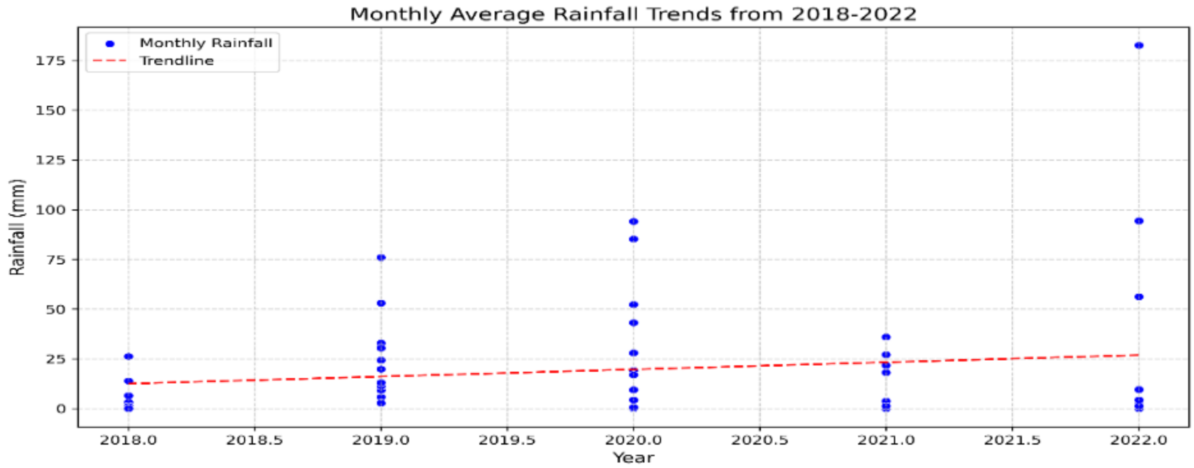

Fig. 3: Monthly average Rainfall trends from 2018-2022

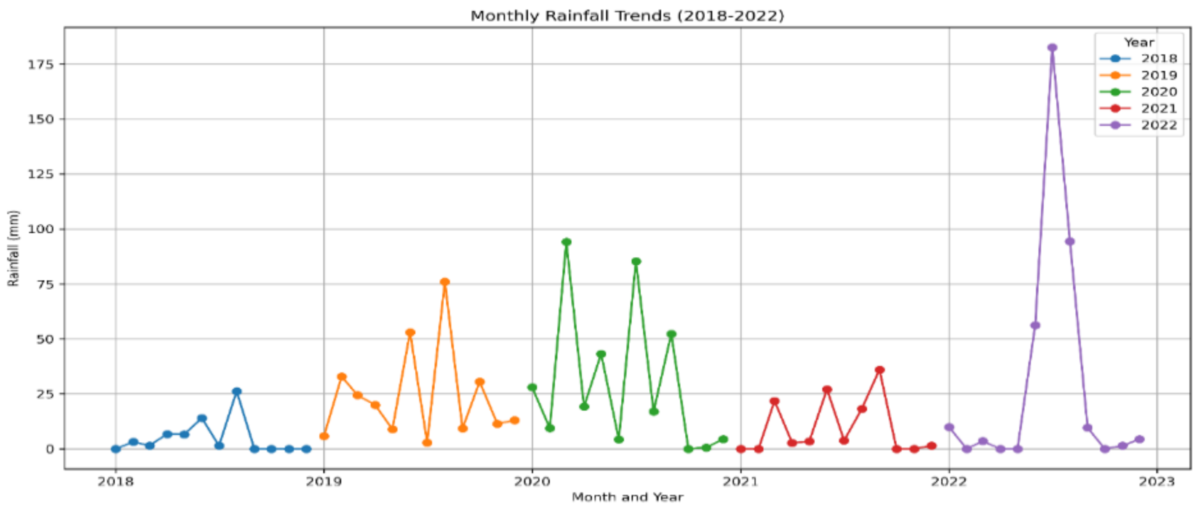

Fig. 4: Monthly Rainfall Trends (2018-2022)

Besides, production information in tons of annual crop yield from the years 2008-09 to 2022-23 was collected. Wheat was selected as the focus crop due to its economic importance and extensive cultivation in Multan, where it covers a significant proportion of the total agricultural land.

Before feeding it to the training set and the test set, slight preprocessing was done to strip the data clean of any inaccuracies. Most values in the rainfall data set were imputed to zero since gaps in the data would mess up the entire analysis. Data that was in alphabetical order, whereby others replaced some values due to non-completion of the questionnaires, were normalized. The parameter of rainfall was in terms of monthly distribution, while the output was required to be in terms of annual accumulation, thus, the monthly numbers were rolled up into annual accumulation for comparison with the crop yields. The monthly data was, however, preserved as the need arose for finer analysis. Additionally, wheat is susceptible to climate variations, making it an ideal crop for studying the impact of temperature and rainfall on yield prediction. This dataset quantified the agricultural yield of the region's main crops and was the forecast's dependent variable. The data were collected from the Bureau of Statistics of the Punjab Government and other publicly available resources [16]. These records were preprocessed using Min-Max normalization before being input into the LSTM model. Data cleaning involved handling missing values, ensuring consistency, and structuring the data for time-series analysis. The datasets were first cleaned and normalized as mentioned earlier, and then merged based on a common "Year" variable, and this merged dataset comprised temperature, rainfall, and

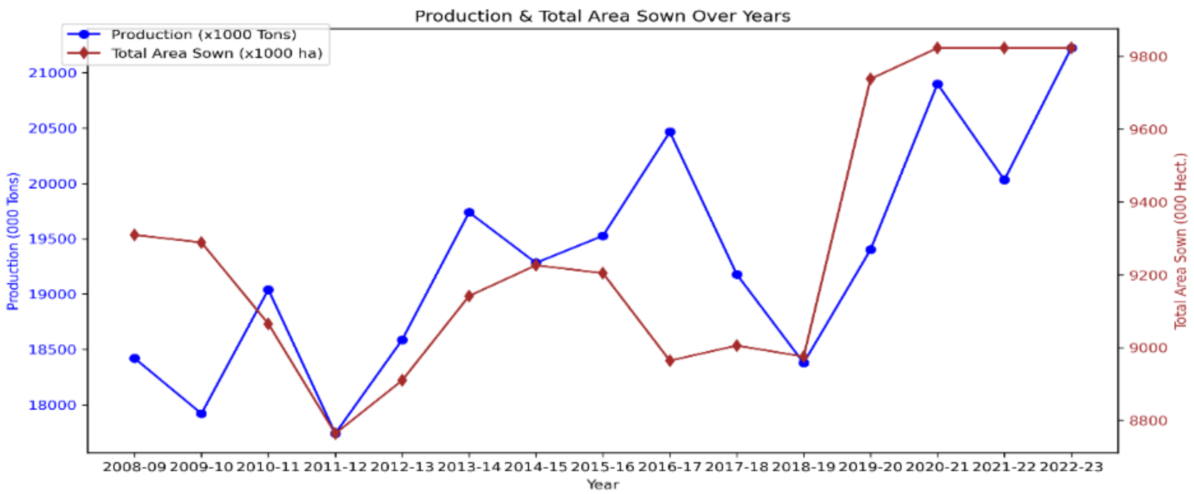

Fig. 5: Production & Total over Years

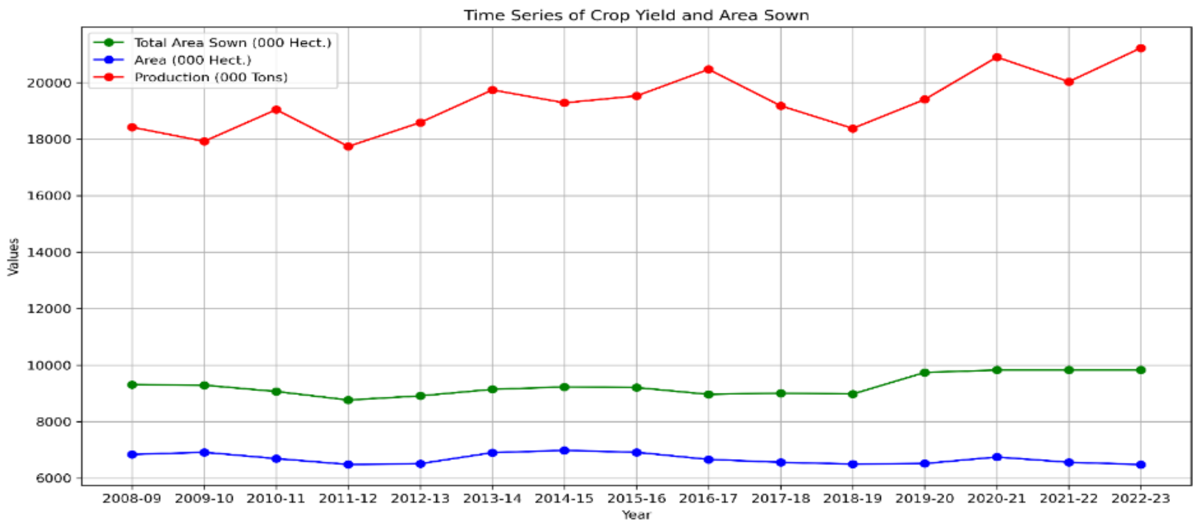

Fig. 6: Time Series of Crop Yield and Area Sown

crop yield data. This integration made it possible to capture all influencing factors to support analysis and modeling. Before feeding it into an LSTM model, normalization was done using the Min-Max

Scaler to get the features in the range of 0-1. This step was crucial to render the model efficient and avoid distorting the values that have large numeric differences, such as annual rainfall values, while comparing with temperature values. Finally, the data was converted into the time series format required by the LSTM model. This structuring entailed using data from the three prior years as independent variables to forecast the yield of crops in the subsequent year. For example, the data on temperature, rainfall, and crop yield collected between the years 2007 and 2009 were employed in the study to predict the crop yield in the year 2010. This approach allowed the model to capture temporal dependencies, which are important to understanding the functioning of agricultural systems. Such a careful approach allowed for not only data cleaning and normalization but also the structuring of the data in a way that can take advantage of the LSTM's inherent strengths, thus making it well suited for yield prediction problems.

Although the data on soil moisture content is extremely essential for estimating a crop's yield, the available datasets for Multan did not include soil moisture data for an extended period. The attempts to acquire remote sensing soil moisture data were capped by poor temporal coverage and low spatial resolution. Thus, this study was limited to the use of temperature and rainfall as the main climate indicators, which is why future work needs to focus on including trustworthy soil moisture datasets when they are made available.

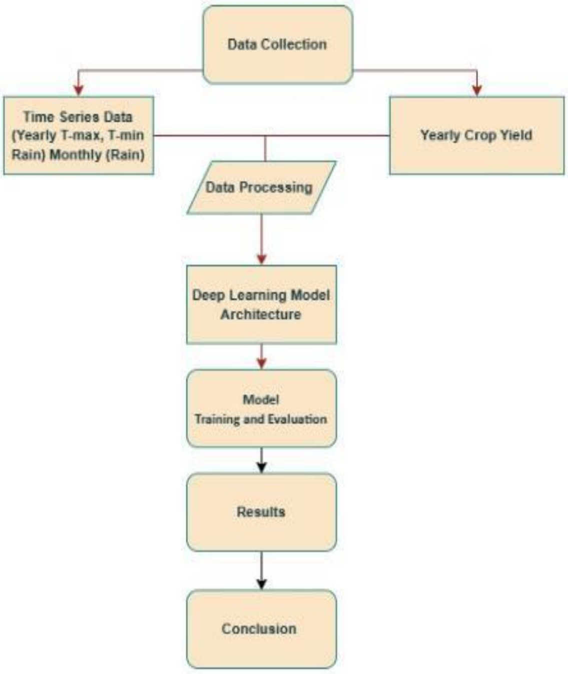

Fig. 7: LSTM Deep Learning Model Methodology Diagram

The percentage of land cultivated out of total available land has declined progressively over time, as suggested in below **Fig. 8**. The reason may be urbanization, land degradation, or policy driven land redistribution.

2.3 Model Architecture

The model architecture used in this study was drawn from Long Short-Term Memory (LSTM) networks, which are ideal for time series forecast. LSTMs are a kind of recurrent neural network (RNN) that has the capability of modeling and learning dependencies or correlation within sequential data hence can be used for making crop yield prediction based on climatic and agricultural history data. The first layer of the model was the LSTM layer with 50 units. This layer was intended to recognize multivariate temporal dependencies in the input signals, with a certain emphasis placed on the previous temperature and rainfall data. The activation function used for this layer was ReLU (Rectified Linear Unit) since it is very useful when addressing problems such as the vanishing gradient, which is prominent in deep networks.

A dropout layer followed the first LSTM layer with a rate set at 20% to minimize overfitting. A Dropout technique is applied to randomly remove partially the neurons during the training stage to reduce over-dependency on the training data and to generalize the model. The second LSTM layer also included 50 units and, similarly to the first LSTM layer, the return sequences were set as False. This configuration makes it possible for the second layer to output a single real value, which is the final predicted crop yield, not a sequence. This was done because the goal of the model was to give a prediction of the yield of the next year's crop by learning the patterns set by the input. Another dropout layer was added after the second LSTM layer to mitigate overfitting, set at a rate of 20%. This layer made the learning process more stochastic so that the model could generalize better to unseen data.

Last, in which fully connected layer consisting of one neuron is added to the model. This layer was tasked with producing the values of the various crop yield forecasts. Fully connected layers are the layers where each neuron is connected to each neuron of the preceding layer. In this case, it returned the result of the model in the form of a single value of crop yield for the given year. As for the optimizer to fine-tune the model, the Adam optimizer was chosen since it is among the most efficient ones for training deep-learning models. The loss function selected for the model was MSE, suitable for linear regression models and which

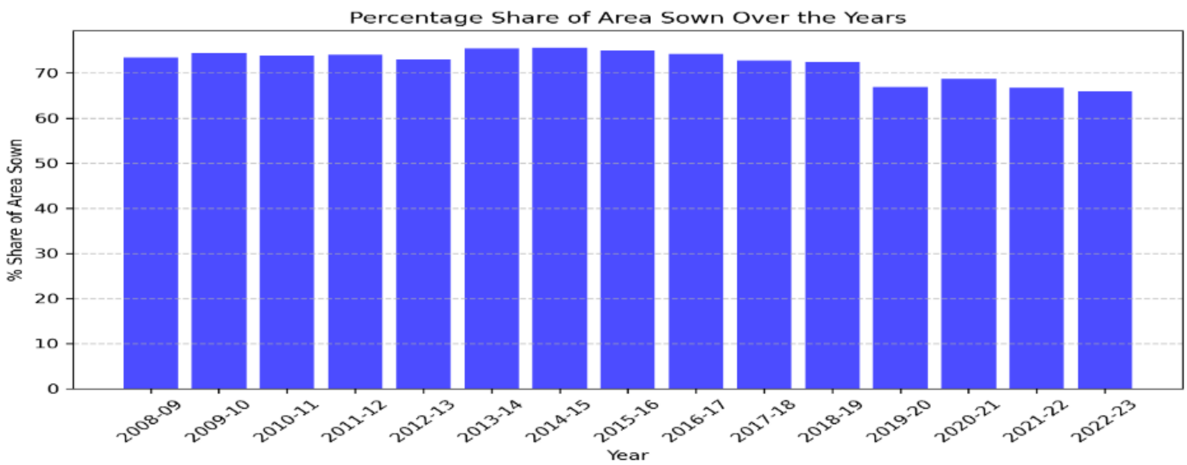

Fig. 8: Percentage share of cultivated area over time, showing trends in land utilization

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 3, 50)	11,000
dropout (Dropout)	(None, 3, 50)	0
lstm_1 (LSTM)	(None, 50)	20,200
dropout_1 (Dropout)	(None, 50)	0
dense (Dense)	(None, 1)	51

Total params: 31,251 (122.07 KB)
Trainable params: 31,251 (122.07 KB)
Non-trainable params: 0 (0.00 B)

Fig. 9: Model Sequential

evaluates the mean of the squared differences of the differences between the predicted and actual values. For assessment, Mean Absolute Error (MAE) was employed, as it calculates the sum of the absolute value of the differences in predicting and actual values divided by the sizes of the samples, which gives a more descriptive measure of the performance of the model. Using this architecture, the required LSTM networks for time-series prediction of crop yields were enhanced combined with the dropout, which helps the model learn from the data sets and does not overfit the data the model is trained on.

2.4 Model Training and Evaluation

The dataset used in this study was split into two parts: a training set (80 percent of data) and a validation set (20 percent of data)>. The data into which the model was trained was obtained from the training set, and the model was tested on the testing set. The size of the batches was set to 16, which means the number of samples that are processed in parallel in one pass forward/backward. The model was trained for 50 epochs thus the model repeated the entire process of going through the training data and modifying its weights 50 times.

To, evaluate the model's performance, two common metrics were used: Mean squared error (MSE) and mean absolute error (MAE). The performances of these metrics are based on the gap between the predicted and the actual crop yield values to determine the accuracy of the model.

Mean Squared Error (MSE) is calculated using the following formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

Where:

- n is the number of test samples
- y_i is the actual value of the i-th sample
- $\hat{y}_i$ is the predicted value for the i-th sample

MSE is particularly useful for identifying large errors, as it squares the difference between the actual and predicted values, making larger errors more penalized.

Mean Absolute Error (MAE) is calculated using the following formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

Where:

- n is the number of test samples
- y_i is the actual value of the i-th sample
- $\hat{y}_i$ is the predicted value for the i-th sample

MAE offers a very clear interpretation of the mean of the absolute difference between the actual and predicted values without making big errors larger than the case with MSE.

Throughout the model training process, both MSE and MAE were observed, thus at the end of the testing section for the model, we noted extremely low figures for MSE and MAE. This indicates that both models were effective in estimating crop yield and that the estimated values are well approximated by the actual crop yield in the test set.

3. Results and Discussion

The performance of the LSTM model in terms of predicting crop yields was analyzed by comparing the predicted yield of the LSTM model with the actual yield of crops obtained from the test dataset. The model again also revealed fair prediction effectiveness; the prediction accuracy was 94.64%; the MAPE 5.36%; the MAE 1136.70; and the RMSE 1136.70. Furthermore, a high level of accordance was witnessed between the actual yield and the one predicted in the model making the latter capable of capturing the temporal dependencies inherent and the nonlinear behavior present in this stochastic process. The efficiency of the model is explained by its increased ability to analyze sequential data and find hidden dependencies in temperature, rainfall, and yield histories. However, it is also in these areas that the results also reveal lessons for improvement. One can only speculate that expanding the range of predictor variables by including soil fertility, irrigation, crop variety, and improved accuracy of meteorological data could improve the model. However, one can utilize different advanced LSTM forms including Bidirectional LSTM or Attention-based LSTMs, and hybrid them with other pure machine learning techniques like Gradient Boosting or Random Forests to enhance the forecasting precision. In total, the findings suggest that LSTM models can be effectively used for agricultural yield prediction in practice. Modeling with larger, more complex datasets requires integration with other large-scale datasets and more advanced statistical methods for further improvement of accuracy and reliability across the range of agricultural situations. Although soil moisture is essential for crop production, there is no reliable data available. This research showed that using temperature and rainfall alone in LSTM models produced 94.64% accurate yield predictions, indicating that the two factors encompass a significant amount of climate impacts on yield. Results shown in below **Fig. 10**.

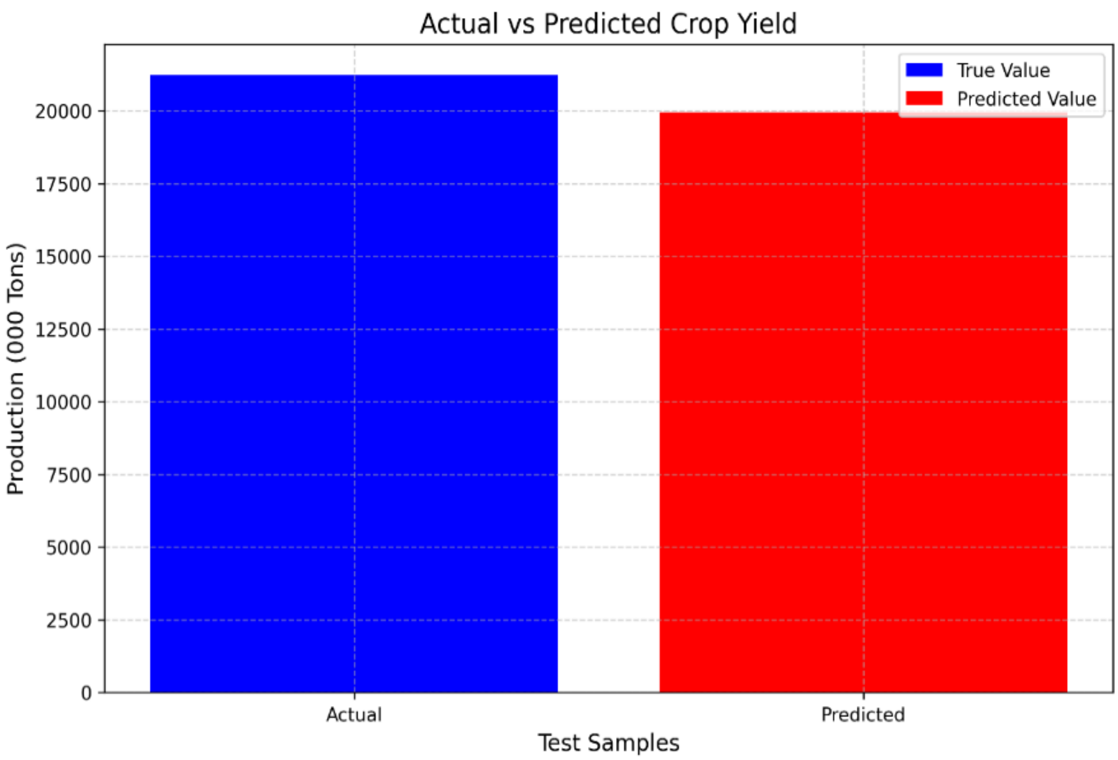

Fig. 10: LSTM Model Prediction Output Actual vs Predicted Crop Yield

Yet, the accurate soil moisture data that was recorded could improve the prediction accuracy and help better allocate water resources in future studies. The graph in **Fig. 11** demonstrates how the area sown shows its pattern together with the production index using 2012-13 as the base year. Index values display variations between both parameters which show times of enhanced efficiency together with instances of lowered agricultural output although land usage remains steady.

4. Conclusion

This study successfully establishes the feasibility of using Long Short-Term Memory (LSTM) models for yield forecasting based on temperature, rainfall, and production history. According to the analysis, the model's variable has high yields, a best fit of 94.64%, a MAPE of 5.36%, and low error metrics to yield forecasting. The paper suggests that LSTM-based models are useful tools for getting insights into busted trends in agriculture to form data-driven decisions for resource allotment, risk management, and food security planning. However, this study also indicates places that research should continue, to improve the general efficiency and effectiveness of supply chains. The various factors that might be useful in the model include soil characteristics, irrigation technique, the kind of crops, and detailed weather conditions amongst others. Other steps can also look for more different predictions via new architectures of LSTM, for example, switching which could be evaluated in one scheme to accomplish different forecasts or using various levels of LSTM. Moreover, testing the presented model in other areas and under different crop conditions would contribute to its applicability. The presented approach can be considered a major step towards the utilization of machine learning for sustainable agriculture. When used to predict accurate yield expectations, LSTM models can reduce the impacts of climate fluctuations and inform antimodel agricultural management, as well as assist in global endeavors to improve food stability following the negative repercussions of climate volatility.

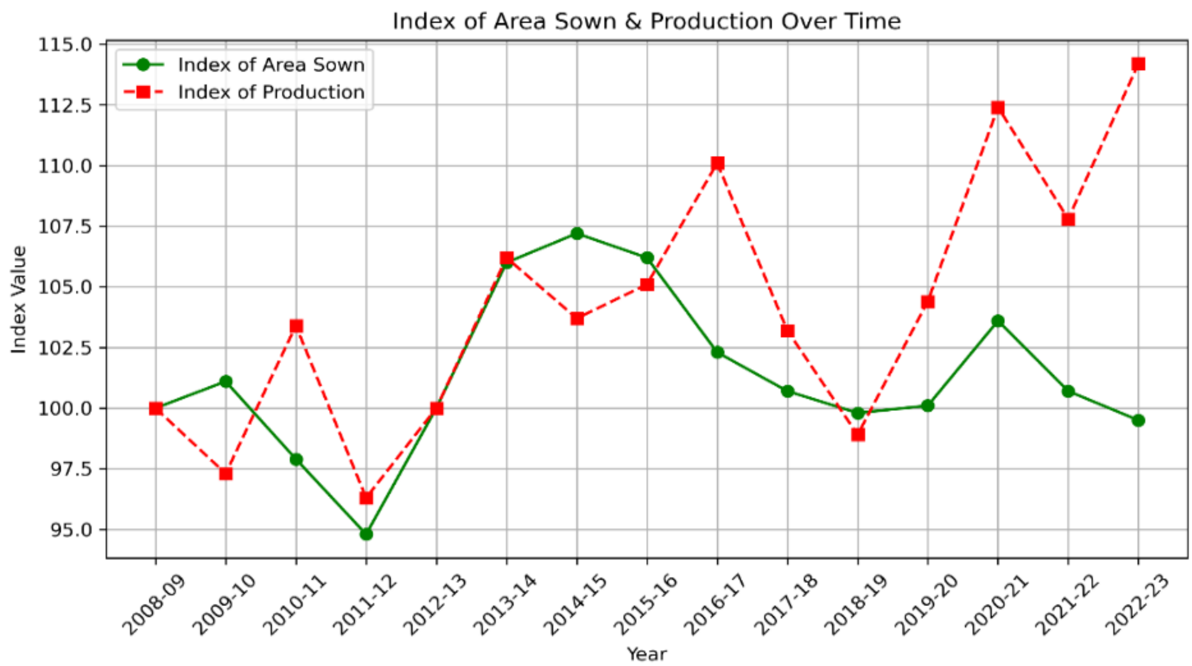

Fig. 11: Trend analysis of area sown and production index (Base Year: 2012-13)

5. Acknowledgment

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