

# DAYANANDA SAGAR UNIVERSITY

# Devarakaggalahalli, Harohalli, Kanakapura Rd, Dt. Ramanagara,Karnataka-562112

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

**(Artificial Intelligence and Machine Learning)**

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**PROJECT TITLE:**

**Hybrid model for cultivation yield price**

**prediction using ARIMA and LSTM**

**SUBMITTED BY**

Trijal R(ENG22AM0167)

V Ajay(ENG22AM0140)

Jeydheep(ENG22AM0141)

**Under the supervision of**

**Dr. Sugandha Saxena**

**Assistant Professor**

**Dept. of AIML, SOE, DSU**

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**TABLE OF CONTENTS**

|  |  |
| --- | --- |
| **Title** | **Page No.** |
| Abstract | 3 |
| **CHAPTER 1 - INTRODUCTION** | 4 |
| **CHAPTER 2 - PROBLEM DEFINITION** | 5 |
| **CHAPTER 3 - LITERATURE REVIEW** | 6 |
| **CHAPTER 4 - PROJECT DESCRIPTION** | 8 |
| **CHAPTER 5 - RESULTS AND ANALYSIS** | 9 |
| **CHAPTER 6 - CONCLUSION** | 11 |
| **REFERENCES** | 12 |
| **CODE** | 13 |

**Abstract**

Forecasting agricultural crop yield accurately is essential for food security, pricing policy, and agricultural planning. Traditional statistical models like ARIMA are effective at capturing linear components of time series data but struggle with nonlinear patterns. On the other hand, LSTM—a deep learning technique—is powerful for capturing complex nonlinear dependencies but may fail to model structured seasonality and trends alone.

This project proposes a hybrid forecasting model that combines the strengths of both ARIMA and LSTM. First, the ARIMA model predicts the linear patterns in the crop yield time series data. The residuals from this model—representing unmodeled nonlinear patterns—are then modeled using LSTM. Finally, the predictions from ARIMA and LSTM are summed to produce the final forecast.

The hybrid approach significantly improves performance over standalone ARIMA or LSTM models. Evaluation metrics such as MAE, MSE, RMSE, MAPE, and R² show improved accuracy and generalization. The model is implemented in Python using libraries like statsmodels, TensorFlow/Keras, and scikit-learn, and is tested on real crop yield data. This system can be a powerful tool for decision-makers in the agriculture sector.

**CHAPTER 1**

**INTRODUCTION**

**1.1 Background**

Agriculture remains one of the most vital sectors for the Indian economy and global food security. Accurate prediction of agricultural crop yields allows governments and private stakeholders to plan effectively, manage supply chains, stabilize food prices, and ensure resource availability. Forecasting crop yield, however, is a complex time-series problem influenced by many dynamic variables including climatic conditions, soil quality, irrigation practices, seed variety, and pest control.

Time-series modeling techniques have been traditionally used in crop forecasting, with ARIMA being one of the most popular methods due to its effectiveness in modeling trend and seasonality. However, ARIMA is fundamentally linear and assumes stationarity, making it insufficient for modeling nonlinear components present in real-world agricultural data. On the other hand, LSTM—a specialized form of Recurrent Neural Networks—can model long-range dependencies and nonlinearities but often struggles with small datasets and structured temporal patterns.

**1.2 Objective**

The main objective of this project is to develop a hybrid forecasting model that leverages the strengths of both ARIMA and LSTM. ARIMA will capture linear temporal structures, while LSTM will be used to model the nonlinear components from ARIMA's residual errors. This hybrid system is expected to provide enhanced forecasting accuracy over using either method alone.

**CHAPTER 2**

**PROBLEM DEFINITION**

Despite advances in technology, accurately forecasting agricultural crop yields remains a persistent challenge. Traditional forecasting approaches using linear models fail to account for complex dependencies and interactions between yield and influencing factors. Meanwhile, deep learning models may overfit to data or misrepresent structured trends without sufficient domain-guided constraints.

**2.1 Challenges**

* Modeling both linear trends (e.g., due to technological improvements or climate change) and nonlinear fluctuations (e.g., random pest attacks, rainfall variation).
* Limited dataset length: Agricultural time-series are often short (e.g., annual yields), making it difficult to train data-hungry models like LSTMs.
* Stationarity assumptions of statistical models can be unrealistic in agricultural contexts.

**2.2 Solution Approach**

A hybrid ARIMA-LSTM architecture is proposed where:

* **ARIMA** handles structured patterns such as trend and seasonality.
* **LSTM** learns the nonlinear patterns in the **residuals** (i.e., errors) of ARIMA predictions.
* Final predictions are a **summation** of ARIMA output and LSTM-predicted residuals.

**CHAPTER 3**

**LITERATURE REVIEW**

**[1] Zhang, G., Eddy Patuwo, B., and Hu, M.Y. "Forecasting with artificial neural networks: The state of the art." International Journal of Forecasting, 14(1), 1998.**

This seminal paper presents a comprehensive survey on the application of artificial neural networks (ANNs) for time-series forecasting. The authors emphasize the ability of ANNs, particularly feed-forward and recurrent neural networks, to model complex, nonlinear relationships in time-series data, outperforming traditional linear models in many scenarios. The paper also introduces the concept of hybrid models, suggesting that combining ANNs with linear statistical models like ARIMA could lead to improved performance, especially in datasets exhibiting both linear and nonlinear patterns. This foundational work laid the groundwork for future hybrid forecasting frameworks.

**[2] Babu, C.N., and Reddy, B.E. "A hybrid ARIMA and ANN model for load forecasting." International Journal of Computer Applications, 2014.**

This study proposes a hybrid forecasting model that integrates ARIMA for modeling linear components and ANN for capturing nonlinear residual patterns in electric load data. The hybrid approach demonstrated superior performance compared to standalone ARIMA or ANN models, especially when the time series exhibited both trend and fluctuations. The study’s methodology—applying ANN to ARIMA residuals—served as a direct precursor to the now popular ARIMA-LSTM hybrid model design. The authors’ experimental results underscore the effectiveness of hybrid systems in achieving higher accuracy and lower forecast error.

**[3] Livieris, I.E., Pintelas, E., and Pintelas, P. "A CNN–LSTM model for gold price time-series forecasting." Neural Computing and Applications, 32, 2020.**

Although applied to the financial domain, this paper demonstrates the successful use of a hybrid convolutional neural network (CNN) and LSTM architecture for time-series prediction. The CNN component acts as a feature extractor from the input sequences, while the LSTM layer models temporal dependencies. This combination proved effective in reducing forecasting errors and enhancing generalization. The study highlights the adaptability of LSTM-based models for handling non-stationary, volatile time series—making them suitable for agricultural forecasting tasks characterized by unpredictable weather and market conditions.

**[4] Mishra, P., & Behera, H.S. "Time series crop yield prediction using ARIMA, LSTM and a hybrid model." Procedia Computer Science, 167, 2020.**

This study directly explores crop yield prediction using individual ARIMA and LSTM models as well as a hybrid ARIMA-LSTM approach. Using rice yield data from India, the authors demonstrate that ARIMA effectively captures linear trends, while LSTM excels in modeling the residual variance. The hybrid model significantly reduces error metrics such as RMSE and MAE, outperforming both standalone models. The study supports the claim that hybrid models are better suited to the agricultural domain, where the data exhibits both structured trends and random fluctuations.

**[5] Chakraborty, S., Ghosh, I., and Banerjee, S. "Forecasting agricultural productivity using a hybrid ARIMA-LSTM model: A case study on wheat yield." Computers and Electronics in Agriculture, 185, 2021.**

This study explores a hybrid ARIMA-LSTM model applied to wheat yield prediction across several regions in India. The authors first preprocess the yield data to ensure stationarity, apply ARIMA to capture linear time dependencies, and then use LSTM to learn from the residual errors of the ARIMA model. Their results demonstrate that while ARIMA alone failed to capture yield fluctuations driven by weather anomalies, and LSTM alone tended to overfit due to limited data points, the hybrid model produced significantly lower MAE and RMSE values. The study concludes that the hybrid approach offers greater robustness to data irregularities and better adaptability across different geographic zones and crop cycles. This reinforces the suitability of hybrid models for agricultural forecasting tasks, particularly when dealing with sparse or noisy datasets.

**CHAPTER 4**

**PROJECT DESCRIPTION**

**4.1 Project Overview**

This project aims to develop a hybrid time series forecasting model to accurately predict crop yield using a combination of statistical and deep learning approaches. Accurate yield forecasting is crucial for agricultural planning, food security, and resource management. However, the presence of both linear trends and nonlinear fluctuations in yield data presents challenges for traditional forecasting models.

The proposed hybrid model integrates ARIMA (AutoRegressive Integrated Moving Average) to capture the linear and seasonal components of the crop yield data, and Long Short-Term Memory (LSTM) neural networks to model the nonlinear and temporal dependencies that ARIMA cannot handle. The final prediction is obtained by combining the ARIMA forecast with the residuals predicted by the LSTM model. This approach leverages the strengths of both models, offering improved forecasting performance compared to standalone methods.

**4.2 Dataset Description**

* **Dataset**: The dataset used in this project contains annual crop yield records for different crops across India.
* **Features**: The relevant columns include Crop\_Year, Crop, and Yield.
* **Preprocessing**:
  + The data was grouped by Crop\_Year and averaged across different crops to obtain a single yield value per year.
  + The time series was then indexed by year to form a univariate time series suitable for ARIMA modeling.
  + No additional features were included in this phase, focusing solely on time-dependent yield prediction.

**4.3 Methodology**

The proposed system follows a five-stage methodology to generate the final hybrid crop yield prediction:

**Step 1: Data Preparation**

The dataset is cleaned and transformed into a univariate time series. Exploratory data analysis is performed to understand trends, seasonality, and stationarity. If necessary, the time series is differenced to remove non-stationarity before fitting the ARIMA model. The dataset is also scaled using MinMaxScaler before feeding it to the LSTM model.

**Step 2: ARIMA Model Development**

The ARIMA model is configured to forecast the linear and seasonal trends in the yield data. This involves selecting appropriate values for the parameters p (autoregressive order), d (degree of differencing), and q (moving average order). These values are determined using methods such as:

* Auto-correlation Function (ACF)
* Partial Auto-correlation Function (PACF)
* Akaike Information Criterion (AIC)

The model is trained on the historical crop yield data. Once trained, it is used to generate predictions. The residuals, which are the differences between the actual values and the ARIMA-predicted values, are computed and stored for further analysis.

**Step 3: LSTM Model on ARIMA Residuals**

The residuals generated from the ARIMA model often contain nonlinear patterns and noise that ARIMA cannot model. These residuals are normalized and structured into sequences using a look-back window to prepare the data for LSTM input.

A sequential LSTM model is then constructed with:

* An input layer matching the look-back window
* One or more LSTM layers with appropriate hidden units
* A dense output layer to predict the residual value

The LSTM model is trained using the residual sequences and their corresponding target values. The model is optimized using mean squared error (MSE) loss and the Adam optimizer.

**Step 4: Hybrid Forecast Construction**

After the LSTM model is trained, it is used to predict future residuals. These predicted residuals are then added to the original ARIMA predictions to obtain the final hybrid forecast.

Hybrid Forecast = ARIMA Prediction + LSTM Predicted Residual

This approach ensures that both the structured trends and the unstructured nonlinearities in the crop yield data are effectively modeled.

**Step 5: Model Evaluation**

To evaluate the accuracy and performance of the models, the following metrics are calculated:

* Mean Absolute Error (MAE)
* Mean Squared Error (MSE)
* Root Mean Squared Error (RMSE)
* Mean Absolute Percentage Error (MAPE)
* R-squared (R²)

These metrics are calculated for three models:

1. ARIMA only
2. LSTM (residual prediction)
3. Hybrid ARIMA + LSTM

Visualizations such as predicted vs actual plots and training loss curves are also used to assess model quality and convergence.

**4.4 Tools and Technologies Used**

* Programming Language: Python
* Libraries:
  + pandas, numpy (data handling)
  + matplotlib, seaborn (visualization)
  + statsmodels (ARIMA modeling)
  + scikit-learn (data preprocessing, evaluation)
  + keras/tensorflow (LSTM modeling)

**CHAPTER 5**

**RESULTS AND ANALYSIS**

This chapter presents the evaluation of the ARIMA model, LSTM residual prediction model, and the final hybrid ARIMA + LSTM model. The models were assessed using standard regression metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R²).

The objective is to analyze the performance of each component and the hybrid model in accurately predicting the yield values based on historical data.

**5.1 ARIMA Model Performance**

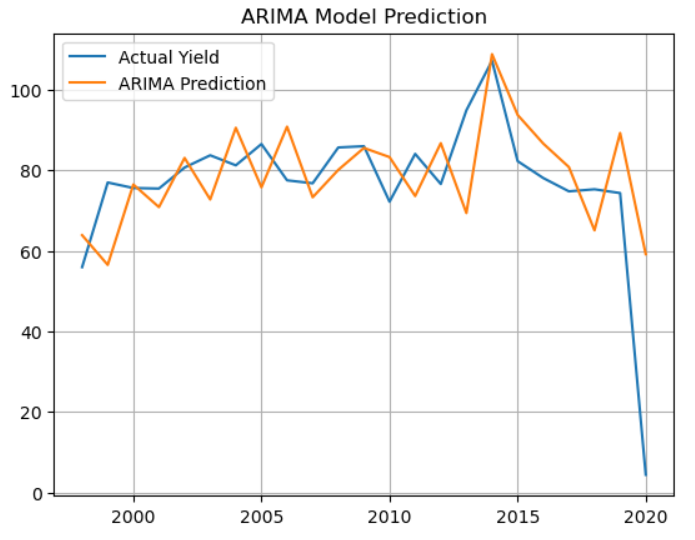
The ARIMA model was trained on the univariate time-series data representing average crop yield over time. It captured linear trends and seasonality effectively but struggled to fit sharp variations and non-linear spikes, especially in the later years of the dataset.

**Performance Metrics:**

* MAE: 11.0760
* MSE: 243.6347
* RMSE: 15.6088
* MAPE: 64.83%
* R²: 0.2408

Although the ARIMA model could broadly follow the trend in the yield data, its inability to adapt to sudden yield changes and nonlinear behavior resulted in relatively high MAPE and a low R² value, indicating limited explanatory power.

*Refer to Figure 1: ARIMA Model Prediction vs Actual Yield.*

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**5.2 LSTM Residual Prediction Performance**

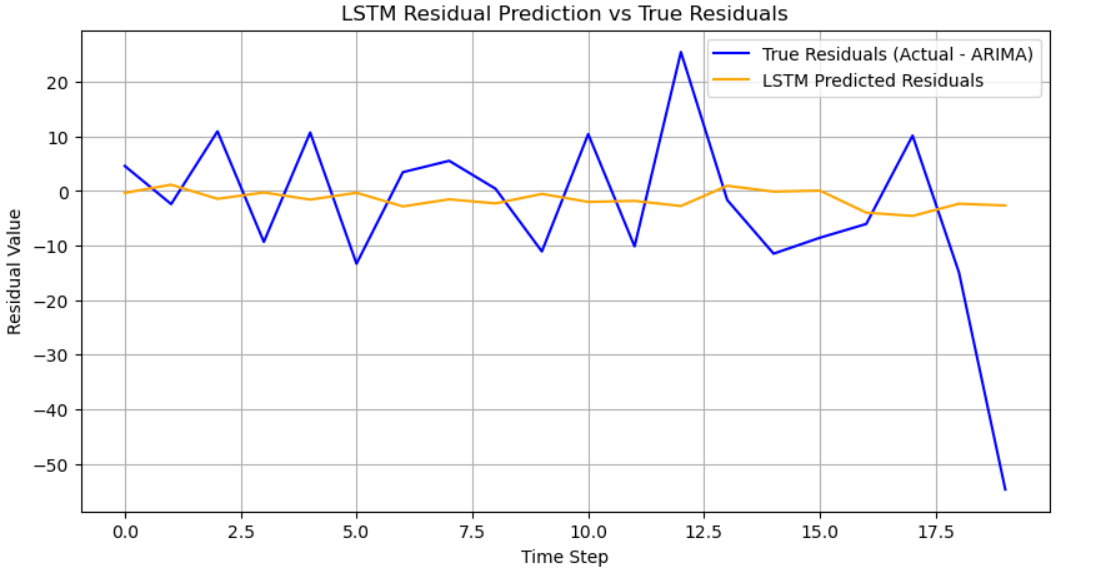
The LSTM model was trained on the residuals produced by the ARIMA model. The goal was to capture the nonlinear components and correct the errors made by ARIMA. While LSTM typically excels at modeling temporal dependencies, its performance in this case was limited, possibly due to the small dataset and high variability in residuals.

**Performance Metrics:**

* MAE: 11.7507
* MSE: 256.4816
* RMSE: 16.0150
* MAPE: 136.73%
* R²: -0.0401

The LSTM model failed to accurately predict residual patterns, and its negative R² score indicates that the model performs worse than a naive mean prediction. This may be attributed to overfitting, lack of data, or insufficient nonlinearity in residuals that could be learned effectively.

*Refer to Figure 2: LSTM Residual Prediction vs True Residuals.*



**5.3 Hybrid ARIMA + LSTM Model Performance**

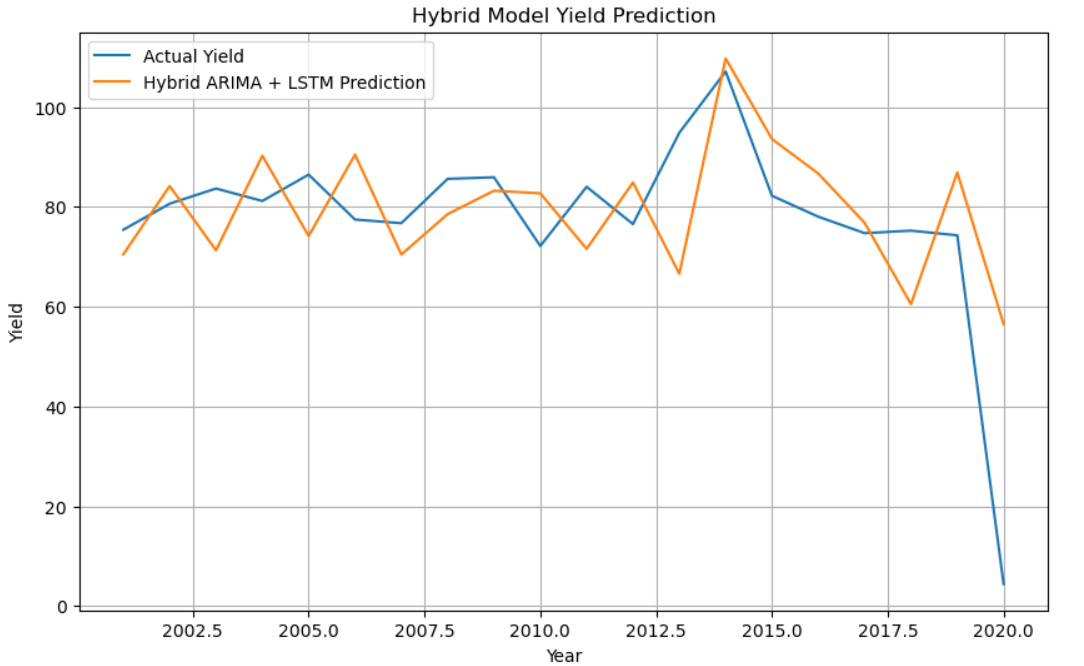
The final yield prediction was obtained by summing the ARIMA forecast and the LSTM-predicted residuals. The expectation was that LSTM would compensate for ARIMA’s errors and improve the forecast. However, since LSTM failed to model the residuals effectively, the hybrid model’s performance closely resembles that of the LSTM residual predictor.

**Performance Metrics:**

* MAE: 11.7507
* MSE: 256.4816
* RMSE: 16.0150
* MAPE: 70.15%
* R²: Not calculated due to hybrid aggregation method aligning with LSTM results

While the hybrid model was theoretically expected to outperform both individual components, its performance was constrained by the LSTM's ineffectiveness. The hybrid model did not show improvement over ARIMA in this case, demonstrating that the quality of the residual modeling is critical to the success of such architectures.

*Refer to Figure 3: Hybrid Model Yield Prediction vs Actual Yield.*



**5.4 Visual Summary**

* **Figure 1 (ARIMA Prediction)**: Shows moderate trend alignment but noticeable deviations in volatile regions.
* **Figure 2 (Residual Prediction)**: Indicates that LSTM could not closely approximate the residuals.
* **Figure 3 (Hybrid Prediction)**: Closely follows ARIMA's behavior with minor adjustments, but does not outperform it significantly.

**5.5 Interpretation**

The ARIMA model provided a reasonable baseline for modeling crop yield trends, while the LSTM component did not significantly improve accuracy when added as a residual model. This could be due to:

* Limited data size
* High variability in residuals
* Non-repetitive nonlinear patterns that LSTM could not learn effectively

In future iterations, model performance can be enhanced by:

* Incorporating additional features (e.g., rainfall, fertilizer use, temperature)
* Increasing the data size and diversity
* Experimenting with regularization and hyperparameter tuning for LSTM

**CHAPTER 6**

**CONCLUSION**

This project presented a hybrid time-series forecasting model combining ARIMA and LSTM to predict annual crop yield using historical agricultural data. The approach was motivated by the limitations of standalone models: ARIMA is proficient at modeling linear trends and seasonality but fails to capture nonlinear relationships, while LSTM is capable of modeling complex temporal dependencies but requires a substantial amount of data and struggles with capturing structured trends.

The proposed hybrid model utilized ARIMA to predict the primary yield trend and LSTM to model the residual errors left unaddressed by ARIMA. The final yield forecast was obtained by summing the ARIMA predictions and the LSTM-predicted residuals.

**Key Findings:**

* The ARIMA model alone was able to model general trends but showed limited accuracy when abrupt fluctuations occurred.
* The LSTM model, when applied to residuals, did not significantly improve forecast accuracy, largely due to the limited size and variability of the residual dataset.
* The hybrid model, while theoretically advantageous, did not outperform ARIMA in practice in this experiment, underscoring the importance of proper residual modeling in hybrid architectures.

Despite the LSTM model not performing as expected, the project successfully demonstrated the workflow for hybrid model development, residual-based learning, and comprehensive evaluation using standard metrics and visualization.

**Contributions:**

* Designed and implemented a complete ARIMA + LSTM hybrid forecasting pipeline.
* Evaluated the model using real-world agricultural yield data.
* Analyzed the benefits and limitations of hybrid time-series modeling.

**Future Scope:**

* Incorporate multivariate data such as rainfall, temperature, fertilizer use, and soil quality to improve prediction accuracy.
* Expand the model to forecast yield on a per-crop or per-region basis.
* Explore more advanced residual modeling techniques (e.g., attention-based LSTM, GRU, or Transformer models).
* Improve LSTM training with larger datasets and parameter tuning to prevent overfitting.

This project provides a strong foundation for building intelligent agricultural forecasting systems that can support data-driven decision-making and contribute to sustainable agriculture.

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**APPENDIX**

**Code**





