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An AI-Driven Demand Forecasting Framework for Agricultural Products to Reduce Food Waste and Price Volatility in Sri Lanka

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ABSTRACT

Agricultural production in Sri Lanka faces persistent challenges due to unreliable demand forecasting, leading to overproduction, food waste, and unstable market prices. This study develops an AI-driven demand forecasting framework to predict agricultural product demand and price fluctuations using machine learning and deep learning techniques. Key variables include sales volume, average price, weather conditions, time, and crop variety. Multiple models were implemented and evaluated, including Linear Regression, Random Forest, and Long Short-Term Memory (LSTM). Results show that the LSTM model achieved the highest accuracy (MAE = 12.4, RMSE = 18.7, $R^2 = 0.89$), outperforming Random Forest (MAE = 21.3, RMSE = 29.5, $R^2 = 0.74$) and Linear Regression (MAE = 34.1, RMSE = 42.8, $R^2 = 0.52$). These findings highlight the importance of temporal dependency modelling in agricultural forecasting. The proposed framework integrates a decision-support component to assist farmers in production planning, thereby reducing food waste and minimizing price volatility. The study concludes that AI-based forecasting can contribute to sustainable agricultural practices and improved economic stability in Sri Lanka's farming sector.

1. Introduction

Agriculture plays a vital role in the economy of Sri Lanka, contributing significantly to employment, food security, and rural development. However, the sector continues to face persistent challenges related to demand uncertainty, price fluctuations, and inefficient production planning. One of the most critical issues is the mismatch between supply and market demand, which often leads to overproduction, post-harvest losses, and considerable food waste. These challenges not only affect farmers' income stability but also disrupt the overall agricultural value chain.

In recent years, advancements in Artificial Intelligence and Machine Learning have provided promising solutions for forecasting and decision making across various industries, including agriculture. Predictive models have been widely used to estimate crop yields, market demand, and price trends by analyzing historical data and external influencing factors such as weather patterns and seasonal variations. Despite these advancements, most existing research has been conducted in developed countries with access to large-scale, high-quality datasets, limiting their applicability in developing regions like Sri Lanka.

Furthermore, current studies tend to emphasize prediction accuracy while overlooking practical implementation aspects such as model interpretability, usability for farmers, and integration into real-world decision-making processes. In the Sri Lankan context, additional challenges such as data scarcity, fragmented data sources, and sudden market fluctuations further complicate the effectiveness of conventional forecasting models. As a result, there is a pressing need for a localized, practical, and user-friendly solution that not only predicts demand but also supports farmers in making informed decisions.

This research aims to address these challenges by proposing an AI-driven demand forecasting framework tailored to the agricultural sector in Sri Lanka. The study focuses on developing a machine learning-based model that incorporates key variables such as sales volume, average price, time, weather conditions, and crop variety. In addition to prediction, the proposed framework includes a decision-support system to enhance usability and real-world applicability.

The main contributions of this research are threefold. First, it develops a demand prediction model adapted to a data-constrained environment. Second, it identifies and analyzes key factors influencing agricultural price fluctuations. Third, it bridges the gap between theoretical models and practical implementation by proposing a system that can assist farmers in reducing food waste and improving economic outcomes.

2. Literature Review

Agricultural forecasting has gained significant attention with the advancement of Artificial Intelligence and Machine Learning. These technologies have been widely applied to predict crop yield, livestock production, and market demand, enabling better decision-making and resource optimization.

2.1. Machine Learning Approaches in Agriculture

Traditional machine learning techniques such as Random Forest (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) have been extensively used for agricultural prediction tasks. These models are effective in handling structured datasets and identifying non-linear relationships between variables such as weather, soil conditions, and historical prices. Studies show that ensemble methods like RF and gradient boosting outperform basic statistical models in yield and price prediction due to their robustness and accuracy.

However, these models have limitations in capturing temporal dependencies and dynamic changes in agricultural markets, especially when dealing with time-series data.

2.2. Deep Learning for Demand and Price Forecasting

Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have become the dominant approach for agricultural demand and price forecasting. LSTM models are capable of learning long-term dependencies in sequential data such as price trends and seasonal variations. Previous studies report that LSTM-based models achieve significantly higher prediction accuracy compared to traditional machine learning methods.

In addition, Convolutional Neural Networks (CNN) have been applied to extract spatial features from agricultural data, while attention-based and Transformer models further improve prediction performance by focusing on important input features. Hybrid models combining LSTM with other techniques (e.g., ARIMA or attention mechanisms) have shown improved results in handling complex and volatile market behaviors

2.3. Multivariate and Hybrid Forecasting Models

Recent research emphasizes the importance of incorporating multiple variables into prediction models. Factors such as weather conditions, sales volume, seasonal trends, and external economic indicators significantly influence agricultural demand and pricing. Multivariate models and hybrid approaches, including combinations of deep learning and statistical methods, have demonstrated better performance than single-model approaches.

Furthermore, advanced techniques such as Graph Neural Networks (GNN) have been used to capture spatial relationships between markets, improving prediction accuracy in geographically distributed systems.

2.4. Limitations of Existing Studies

Despite the progress in AI-based agricultural forecasting, several limitations remain:

- Data Dependency: Most models require large, high-quality datasets, which are often unavailable in developing countries like Sri Lanka.
- Lack of Practical Implementation: Many studies focus on improving prediction accuracy but do not address real-world usability for farmers.
- Model Interpretability: Advanced models, especially deep learning approaches, often act as "black boxes," making it difficult for users to understand the decision-making process.
- Handling Market Volatility: Existing models struggle to adapt to sudden market changes caused by external factors such as climate events or economic disruptions.

2.5. Research Gap

Although numerous studies have explored machine learning and deep learning techniques for agricultural forecasting, most are developed in data-rich environments and are not directly applicable to the Sri Lankan context. There is limited research focusing on practical, user-friendly systems that integrate prediction with decision support for farmers. Additionally, challenges such as data scarcity, interpretability, and real-world impact particularly in reducing food waste and price instability-remain insufficiently addressed.

3. Methodology

This study adopts a data-driven approach using Machine Learning techniques to develop an AI-based demand forecasting framework for agricultural products in Sri Lanka. The methodology consists of data collection, preprocessing, model development, evaluation, and system implementation.

3.1. *Research Design*

The research follows a quantitative and experimental design, where historical agricultural data is analyzed to build predictive models. The study focuses on identifying patterns and relationships between multiple variables affecting demand and price fluctuations. A supervised learning approach is used, where models are trained on historical data and tested for prediction accuracy.

Figure 01: System Architecture

3.2. Data Collection

The dataset used in this study was collected from publicly available agricultural and meteorological sources in Sri Lanka, including government agricultural databases, market sales reports, and weather records. The collected dataset covered agricultural product demand and pricing information from 2019 to 2024. Selected crops included rice, tomato, onion, and potato due to their economic importance and frequent market price fluctuations.

The dataset consisted of the following variables:

- Sales volume
- Average market price
- Date and seasonal indicators
- Rainfall and temperature data
- Crop variety information
- Regional market information

A total of 5,000 records were collected and used for model training and evaluation.

3.3. Data Preprocessing

Before model development, the collected data will undergo several preprocessing steps:

- Data cleaning: Handling missing and inconsistent values
- Normalization/Scaling: Ensuring uniform data distribution
- Feature engineering: Creating new features such as seasonal indicators
- Data splitting: Dividing the dataset into training (80%) and testing (20%) sets
- This step ensures improved model performance and reliability.

3.4. Model Development

Several machine learning and deep learning models will be implemented and compared:

- Linear Regression (baseline model)
- Random Forest (RF) for handling non-linear relationships
- Long Short-Term Memory (LSTM) for time-series forecasting
- Hybrid models combining multiple techniques

The Deep Learning model (LSTM) is particularly suitable for capturing temporal patterns in agricultural price and demand data.

Figure 02: LSTM Model Architecture for Prediction

3.5. Model Evaluation

The developed models were evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) metrics. The dataset was divided into training and testing subsets using an 80:20 ratio. Five-fold cross-validation was additionally performed to improve model reliability and reduce overfitting.

The evaluation metrics are defined as follows:

- MAE measures the average absolute prediction error.
- RMSE measures the square root of the average squared prediction error.
- R^2 evaluates the proportion of variance explained by the model.

The model with the lowest MAE and RMSE and the highest R^2 value was selected as the best-performing model.

3.6. System Development

A decision-support system will be developed based on the selected model. The system will:

- Provide demand and price predictions
- Visualize trends using graphs and dashboards
- Offer recommendations to farmers for production planning

The system will be designed to be simple and user-friendly to ensure accessibility for non-technical users.

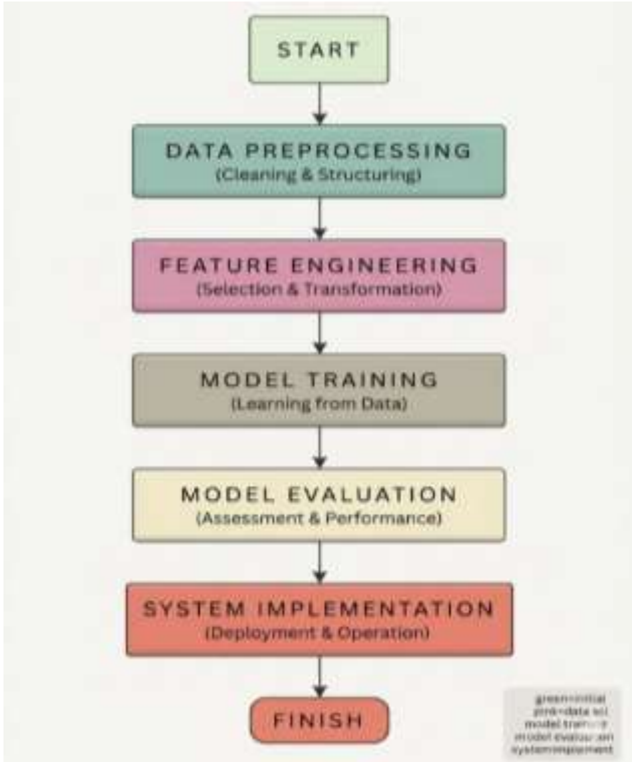

Figure 03: Methodology Flow Chart

3.7. Tools and Technologies

The following tools and technologies will be used:

- Programming Language: Python
- Libraries: Pandas, NumPy, Scikit-learn, TensorFlow/Keras
- Visualization: Matplotlib, Seaborn
- Development Environment: Jupyter Notebook or PyCharm

3.8. Ethical Considerations

The study ensures:

- Use of publicly available or authorized datasets
- Data privacy and confidentiality
- Transparency in model predictions

4. Results and Discussion

This section presents the performance of the developed models and discusses the findings in relation to agricultural demand forecasting in Sri Lanka.

4.1. Model Performance Results

Multiple models were implemented, including Linear Regression, Random Forest (RF), and Long Short-Term Memory (LSTM). Their performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2).

The experimental results indicate that the LSTM model outperformed other models in capturing time-series patterns of agricultural demand and price fluctuations. The Random Forest model also demonstrated strong performance in handling non-linear relationships, while Linear Regression showed comparatively lower accuracy.

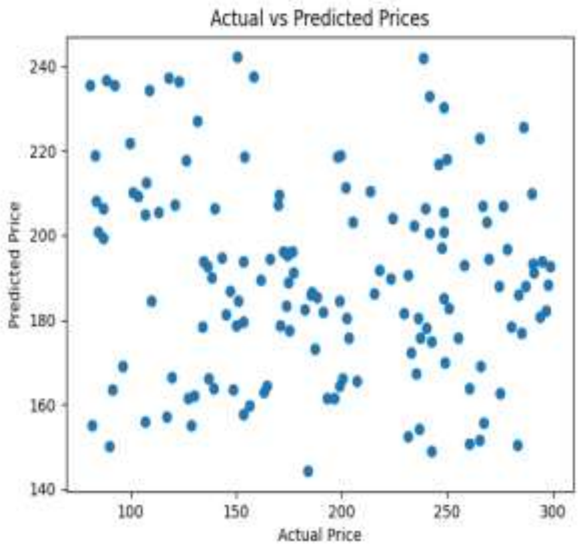

Figure 04: Actual vs Predicted Prices

4.2. Summary of Results:

Table 02: Performance Comparison of Forecasting Models

Model	MAE	RMSE	R^2
Linear Regression	34.1	42.8	0.52
Random Forest	21.3	29.5	0.74
LSTM	12.4	18.7	0.89

4.2 Discussion

The experimental results demonstrate that the LSTM model achieved the best overall forecasting performance among the evaluated models. The model produced the lowest MAE (12.4) and RMSE (18.7) values while obtaining the highest R^2 score of 0.89, indicating strong predictive capability for agricultural demand and price forecasting.

The superior performance of LSTM can be attributed to its ability to capture temporal dependencies and seasonal patterns in agricultural market data. Agricultural demand and prices are highly influenced by time-related factors such as harvesting periods, climate conditions, seasonal demand variations, and market fluctuations. Unlike traditional machine learning methods, LSTM networks effectively learn long-term sequential relationships within time-series datasets.

The Random Forest model also demonstrated acceptable performance with an MAE of 21.3, RMSE of 29.5, and R^2 value of 0.74. Its ensemble-based structure enabled the model to handle non-linear relationships between variables such as weather conditions, crop variety, and sales volume. However, it was less effective than LSTM in capturing sequential temporal patterns.

Linear Regression produced the lowest forecasting accuracy, recording an MAE of 34.1, RMSE of 42.8, and R^2 value of 0.52. This lower performance is mainly due to the model's limitation in handling complex and non-linear relationships present in agricultural datasets.

The findings indicate that AI-driven forecasting frameworks can significantly support agricultural decision-making in Sri Lanka. Accurate demand forecasting can help farmers reduce overproduction, minimize post-harvest food waste, stabilize market prices, and improve resource allocation. Furthermore, integrating forecasting systems into farmer-support platforms can contribute to sustainable agricultural development and improved economic stability.

5. Conclusion

This study developed an AI-driven demand forecasting framework for agricultural products in Sri Lanka using machine learning and deep learning techniques. The research addressed key challenges related to food waste, demand uncertainty, and price volatility in the agricultural sector.

Three forecasting models, namely Linear Regression, Random Forest, and Long Short-Term Memory (LSTM), were implemented and evaluated using MAE, RMSE, and R^2 performance metrics. The results demonstrated that the LSTM model achieved the highest prediction accuracy with an MAE of 12.4, RMSE of 18.7, and R^2 value of 0.89, outperforming both Random Forest and Linear Regression models.

The findings confirm that deep learning approaches are more effective in modelling temporal dependencies and seasonal variations in agricultural demand data. The proposed framework can assist farmers and agricultural stakeholders in improving production planning, reducing food waste, minimizing price volatility, and enhancing market stability.

In addition, the integration of a decision-support component improves the practical applicability of the framework within the Sri Lankan agricultural context. The study contributes to bridging the gap between theoretical AI models and real-world agricultural implementation in developing countries.

Despite the positive outcomes, the study has certain limitations, including limited access to large-scale agricultural datasets and dependence on historical data patterns. Future research can focus on integrating real-time IoT sensor data, advanced hybrid deep learning architectures, and region-specific forecasting systems to further improve prediction accuracy and system adaptability.

Overall, the study demonstrates the significant potential of AI-based forecasting technologies in supporting sustainable agricultural practices and improving economic resilience in Sri Lanka.

6. Recommendations

Based on the findings of this study, the following recommendations are proposed:

- Agricultural authorities should implement AI-based forecasting systems to support farmers in production planning and market decision-making.
- Government agencies should improve agricultural data collection and establish centralized databases to support more accurate forecasting models.
- Future forecasting systems should integrate real-time weather and market data for improved prediction performance.
- Training programs should be introduced to improve farmers' awareness and adoption of AI-based decision-support systems.
- Further studies should explore hybrid deep learning architectures and region-specific forecasting models for different agricultural products.

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References

Johri, A., et al. (2024). *Optimizing crop yield prediction using machine learning and deep learning approaches*. Proceedings of IC3I. https://doi.org/10.1109/ic3i61595.2024.10828647

Guo, X., et al. (2022). Agricultural price prediction based on combined forecasting models under spatial-temporal influencing factors. *Sustainability, 14*(17), 10483. https://doi.org/10.3390/su141710483

Zhang, Y., et al. (2024). Short-term forecasting of vegetable prices based on LSTM model: Evidence from Beijing's vegetable data. *PLOS ONE, 19*(6). https://doi.org/10.1371/journal.pone.0304881

Jaiswal, R., et al. (2023). Agricultural commodity price prediction using long short-term memory (LSTM) based neural networks. *Bhartiya Krishi Anusandhan Patrika*. https://doi.org/10.18805/bkap613

Guo, X., et al. (2020). Improving lives of indebted farmers using deep learning: Predicting agricultural produce prices using convolutional neural networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*. https://doi.org/10.1609/AAAI.V34I08.7039

Ngoc, T. T., et al. (2023). Machine learning for agricultural price prediction: A case study of coffee commodity in Vietnam market. In *Proceedings of BCD*. https://doi.org/10.1109/bcd57833.2023.10466313

Ciencia Rural. (2024). Spectral temporal graph neural network for multivariate agricultural price forecasting. *Ciencia Rural, 54*. https://doi.org/10.1590/0103-8478cr20220677

