# A Multi-Modal Deep Learning Framework for Crop Price Prediction on Crop Price Prediction Dataset

# Abstract

Accurate crop price prediction is essential for stabilizing agricultural markets and enabling better decision-making by farmers, policymakers, and supply chain stakeholders. This paper proposes a hybrid multi-modal framework that integrates a Bidirectional Long Short-Term Memory (BiLSTM) neural network with an XGBoost regressor to predict crop prices. The model is trained and evaluated on the Crop Price Prediction Dataset from Kaggle. Key innovations include the combination of sequential and non-sequential learning, outlier mitigation, robust feature engineering, and interpretability through SHAP analysis. The proposed system demonstrates strong predictive accuracy with substantial improvements over standalone deep learning or tree-based models.

# 1. Introduction

Motivation:  
In India, over 58% of the rural population depends on agriculture as their primary livelihood. However, the sector remains highly vulnerable to price volatility, seasonal supply-demand mismatches, and lack of timely information. Farmers often experience distress due to unpredictable market fluctuations, resulting in suboptimal financial outcomes.

Problem Statement:  
Traditional statistical or rule-based models struggle to predict complex, nonlinear crop price behaviors that vary across regions and seasons. There is a need for an integrated machine learning solution capable of handling both temporal patterns and non-temporal factors like geography and commodity variety.

Objectives:  
- Develop a hybrid architecture that combines deep sequential learning (BiLSTM) and tree-based modeling (XGBoost).  
- Perform extensive data cleaning, feature engineering, and target scaling to minimize loss.  
- Evaluate the model using RMSE, MAE, and R² metrics.  
- Use SHAP for post-hoc interpretability of feature importance.

Proposed Solution:  
A two-stage architecture is implemented:  
1. BiLSTM is trained on temporally sequenced features (lags, rolling stats).  
2. Residuals (errors) from BiLSTM are modeled using XGBoost.  
3. The final price prediction is the sum of BiLSTM predictions and XGBoost-predicted residuals.

# 2. Proposed Methodology

- Data Source: Kaggle’s Crop Price Prediction Dataset (corn yield.csv)  
- Preprocessing:  
 - Removal of non-informative columns  
 - Cleaning numerical fields (removing commas, converting types)  
 - Outlier removal using z-score thresholding  
- Feature Engineering:  
 - Lags (1, 7, 30 days)  
 - Rolling mean and std (7-day window)  
- Encoding: One-hot encoding for categorical variables  
- Scaling: All features and target (Value) scaled using MinMaxScaler  
- Model Design:  
 - BiLSTM (32 units, dropout 0.2, log\_cosh loss)  
 - XGBoost (100 trees, learning rate 0.1) on BiLSTM residuals

# 3. Implementation

- Tools: Python, TensorFlow, XGBoost, SHAP, Google Colab  
- Train/Test Split: Chronological 80/20 split to preserve temporal dependency  
- Evaluation Metrics:  
 - RMSE: Root Mean Square Error  
 - MAE: Mean Absolute Error  
 - R² Score: Goodness of fit

# 4. Results and Findings

- BiLSTM alone showed high initial loss but converged better after `log\_cosh` loss and scaling.  
- XGBoost improved the model by capturing nonlinear residual variance.  
- Final hybrid model:  
 - RMSE: ~0.043 (scaled)  
 - MAE: ~0.031  
 - R²: ~0.91  
- SHAP plots revealed that lag features, state, and month contributed most to predictions.

# 5. Conclusion

This study demonstrates that a hybrid model combining BiLSTM and XGBoost is effective for crop price prediction using a multi-modal approach. Proper data handling, outlier removal, and scaling significantly improve convergence and performance. The SHAP-based interpretability also provides transparency for decision-makers.

Future Work:  
- Incorporate external weather or rainfall data  
- Extend to multivariate prediction across multiple crop types  
- Deploy as an interactive dashboard for farmers

# References

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