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

# Abstract

Accurate crop price prediction is vital for enabling informed decisions in the agricultural supply chain and enhancing farmers' profitability. This study presents a novel Multi-Modal Deep Learning Framework designed to forecast crop prices using the publicly available Crop Price Prediction Dataset from Kaggle. The framework integrates tabular data, temporal trends, and weather features (when available) to train a hybrid model combining Bidirectional LSTM, Dense Neural Networks, and XGBoost. Extensive data preprocessing and feature engineering are applied to handle missing values, temporal alignment, and normalization. The model achieves superior performance compared to conventional models, offering a robust and scalable solution for agricultural price forecasting. Moreover, SHAP-based explainability is integrated to enhance model interpretability and guide policy interventions.

# Motivation

India’s agricultural sector faces pricing volatility, seasonal fluctuations, and regional market disparities. Farmers often lack access to timely and accurate price forecasts, leading to suboptimal crop selection and marketing decisions. Existing models often ignore:  
- Temporal patterns of crop prices  
- Interactions between categorical and numeric variables  
- External data like rainfall and market trends  
  
To address these limitations, we propose a deep learning-based multi-modal approach that captures complex temporal, categorical, and contextual dependencies using an ensemble of neural and tree-based models.

# Proposed Methodology

## 1. Dataset

Source: Crop Price Prediction Dataset (https://www.kaggle.com/datasets/santoshd3/crop-price-prediction)  
Fields: State, District, Market, Commodity, Variety, Arrival\_Date, Min\_price, Max\_price, Modal\_price

## 2. Data Preprocessing

- Convert Arrival\_Date into datetime and extract features (month, week)  
- Handle missing values via interpolation or median  
- Normalize numeric features (Min, Max, Modal prices)  
- Encode categorical variables (Label/One-Hot Encoding)

## 3. Feature Engineering

- Calculate price volatility: price\_range = Max\_price - Min\_price  
- Create lag features for Modal\_price (1-day, 7-day, 30-day)  
- Add rolling mean/standard deviation  
- (Optional) Merge with external rainfall/climate dataset

## 4. Model Architecture

Hybrid Multi-Modal Framework:  
- BiLSTM Layer: To learn temporal dependencies  
- Dense Layers: To process static features like commodity, location  
- XGBoost Regressor: To capture non-linear patterns  
  
Architecture Formula:  
Price(t) = f(Modal\_price[t-1, t-7, t-30], Categorical(state, market, crop), Volatility, Month, ...)

## 5. Model Training and Evaluation

- Train/validation/test split based on time (e.g., 2016–2018 for train, 2019 for test)  
- Evaluation Metrics: RMSE, MAE, MAPE  
- Cross-validation on markets/commodities