Agri-Predict: An AI-Driven Framework for Intelligent Crop Price Forecasting Using Machine Learning and Time-Series Analysis

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Abstract—**Agri-Predict presents a novel hybrid deep learning framework for crop price prediction, designed to address the critical need for accurate forecasting to stabilize agricultural markets and ensure farmer financial security. The proposed system leverages a multi-model approach that integrates three complementary predictive architectures: a Long Short-Term Memory (LSTM) network for capturing complex temporal dependencies and long-term price trends from historical time-series data, an XGBoost regressor for effectively modeling non-linear relationships and handling heterogeneous feature interactions from diverse input variables such as weather patterns, soil conditions, and macroeconomic indicators, and a hybrid LSTM and XGBoost model that synergistically combines the sequential learning capabilities of LSTM with the robust gradient-boosting power of XGBoost. This hybrid architecture enables the system to extract deep temporal features through LSTM layers before passing them to XGBoost for refined final prediction, achieving superior forecasting accuracy over individual models. Extensive evaluation demonstrates that the hybrid LSTM and XGBoost approach significantly outperforms standalone LSTM, XGBoost, and traditional baselines like ARIMA, delivering substantial reductions in error metrics such as RMSE and MAPE. By translating complex, multidimensional data into actionable price intelligence through an accessible interface, Agri-Predict serves as a comprehensive decision-support tool for farmers, policymakers, and supply chain stakeholders, helping reduce price volatility, minimize post-harvest losses, and enhance profitability in the agricultural sector.**

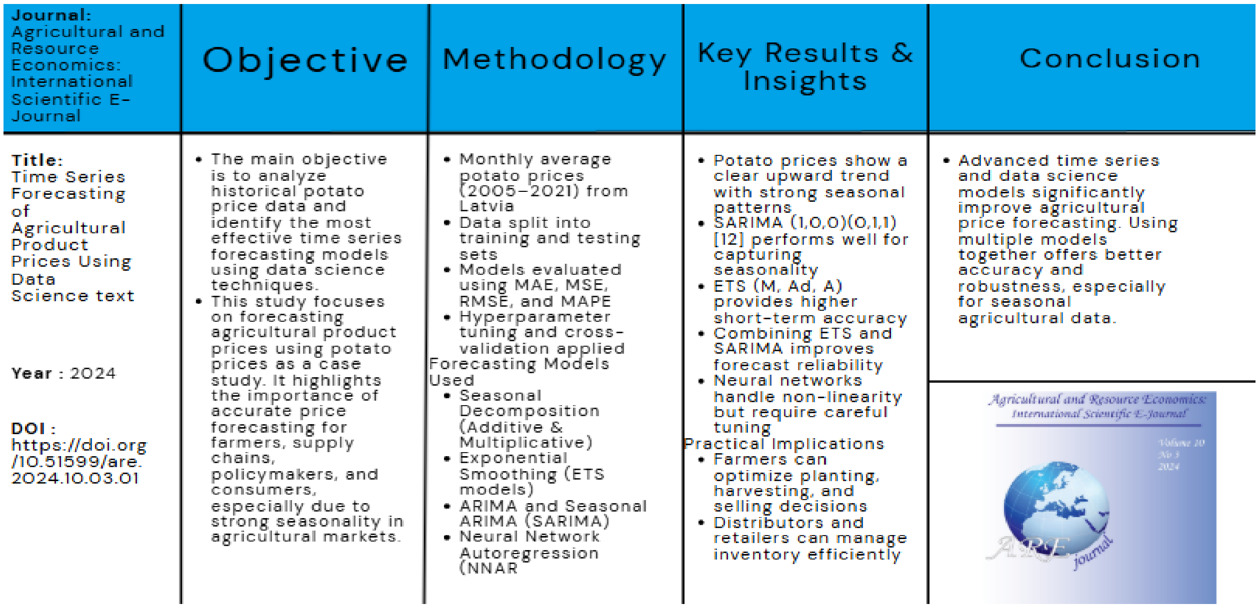
Index Terms—**Crop Price Prediction, Long Short-Term Memory (LSTM), XGBoost, Hybrid Deep Learning, Time Series Forecasting, Agricultural Informatics.**

I. INTRODUCTION

Welcome, did you know that farmers often have to sell their crops at market prices they can't predict? This uncertainty leaves them vulnerable to volatile market fluctuations, forcing many to make planting decisions based on guesswork rather than reliable data. A sudden price drop at harvest time can erase months of hard work, pushing small-scale farmers into financial distress and perpetuating cycles of instability in agricultural communities. Our project, Agri-Predict: The Crop Price Predictor, tackles this challenge head-on. By harnessing the power of advanced machine learning techniques, specifically Long Short-Term Memory (LSTM) networks, XGBoost, and a hybrid LSTM and XGBoost architecture. We analyze diverse datasets, including historical price trends, weather patterns, soil conditions, and macroeconomic indicators. This multi-dimensional approach enables us to generate accurate, reliable crop price forecasts with significantly lower error than traditional prediction methods. What sets Agri-Predict apart is its ability to translate complex data into actionable intelligence. Farmers can access timely price forecasts through an intuitive interface, empowering them to make informed decisions about what to plant, when to harvest, and where to sell for maximum profitability. Policymakers and supply chain stakeholders also benefit from early insights into market trends, enabling proactive interventions to stabilize prices and reduce post-harvest losses. Ultimately, Agri-Predict transforms uncertainty into a strategic advantage. We're not just predicting prices; we're cultivating smarter farming, one forecast at a time.

II. LITERATURE REVIEW OF EXISTING SYSTEMS

The main objective is to analyze historical potato price data and identify the most effective time series forecasting models using data science techniques. The methodology includes: Monthly average potato prices (2005–2021) from Latvia. Data split into training and testing sets, Models evaluated using MAE, MSE, RMSE, and MAPE, Hyperparameter tuning and cross-validation applied, Forecasting Models Used, Seasonal Decomposition (Additive & Multiplicative). Exponential Smoothing (ETS models), ARIMA and Seasonal ARIMA (SARIMA), Neural Network Autoregression (NNAR). Advanced time series and data science models significantly improve agricultural price forecasting.



Journal: Agricultural and Resource Economics: International Scientific E-Journal	Objective	Methodology	Key Results & Insights	Conclusion
Title: Time Series Forecasting of Agricultural Product Prices Using Data Science text **Year** : 2024 **DOI** : https://doi.org/10.51599/are.2024.10.03.01	• The main objective is to analyze historical potato price data and identify the most effective time series forecasting models using data science techniques. • This study focuses on forecasting agricultural product prices using potato prices as a case study. It highlights the importance of accurate price forecasting for farmers, supply chains, policymakers, and consumers, especially due to strong seasonality in agricultural markets.	• Monthly average potato prices (2005–2021) from Latvia • Data split into training and testing sets • Models evaluated using MAE, MSE, RMSE, and MAPE • Hyperparameter tuning and cross-validation applied Forecasting Models Used • Seasonal Decomposition (Additive & Multiplicative) • Exponential Smoothing (ETS models) • ARIMA and Seasonal ARIMA (SARIMA) • Neural Network Autoregression (NNAR	• Potato prices show a clear upward trend with strong seasonal patterns • SARIMA (1,0,0)(0,1,1)[12] performs well for capturing seasonality • ETS (M, Ad, A) provides higher short-term accuracy • Combining ETS and SARIMA improves forecast reliability • Neural networks handle non-linearity but require careful tuning Practical Implications • Farmers can optimize planting, harvesting, and selling decisions • Distributors and retailers can manage inventory efficiently	• Advanced time series and data science models significantly improve agricultural price forecasting. Using multiple models together offers better accuracy and robustness, especially for seasonal agricultural data.

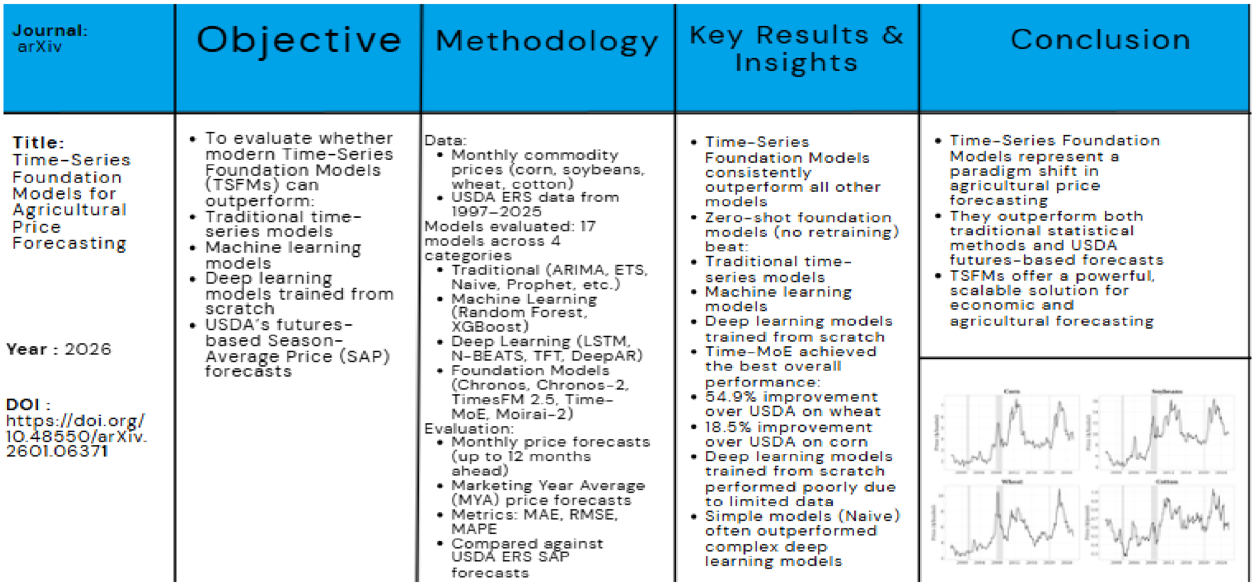
Fig.1: The Literature Review of Time Series Forecasting of Agricultural Product Prices Using Data Science text

Using multiple models together offers better accuracy and robustness, especially for seasonal agricultural data. Recent advancements in agricultural price forecasting have highlighted the growing importance of artificial intelligence and machine learning techniques in improving prediction accuracy and decision-making. The study on Time-Series Foundation Models for Agricultural Price Forecasting demonstrates that modern Time-Series Foundation Models (TSFMs) significantly outperform traditional statistical models, machine learning models, and deep learning models trained from scratch. Using USDA ERS data from 1997 to 2025, the study evaluated 17 models across multiple categories and found that foundation models such as Time-MOE achieved substantial improvements, including a 54.9% increase in forecasting accuracy for wheat and 18.5% for corn compared to USDA forecasts. Furthermore, the study revealed that zero-shot foundation models, which do not require retraining, can outperform conventional approaches, although deep learning models showed limitations due to insufficient data availability (Mahale, 2025).

In the context of developing countries, particularly India, machine learning-based approaches have been widely applied for crop price prediction. A study by Joshi (2025) proposed a comprehensive framework integrating environmental, economic, and logistical factors using datasets from Agmarknet and Kaggle. The research evaluated models such as Linear Regression, Support Vector Regression (SVR), Random Forest, and XGBoost, concluding that XGBoost achieved the highest performance with an R^2 value of 0.988, demonstrating its capability to capture complex nonlinear relationships. The study also identified key determinants of price variation, including demand–supply dynamics and transportation costs, while environmental factors indirectly influenced prices through supply fluctuations. Similarly, Bagonza (2025) explored machine learning-based crop price prediction using historical agricultural data and emphasized the limitations of traditional statistical models in capturing nonlinear price patterns. The study applied models such as Support Vector Machines and Random Forest and found that ensemble and nonlinear approaches significantly improved prediction accuracy. It further highlighted that proper feature selection and historical trend analysis play a crucial role in enhancing forecasting performance.

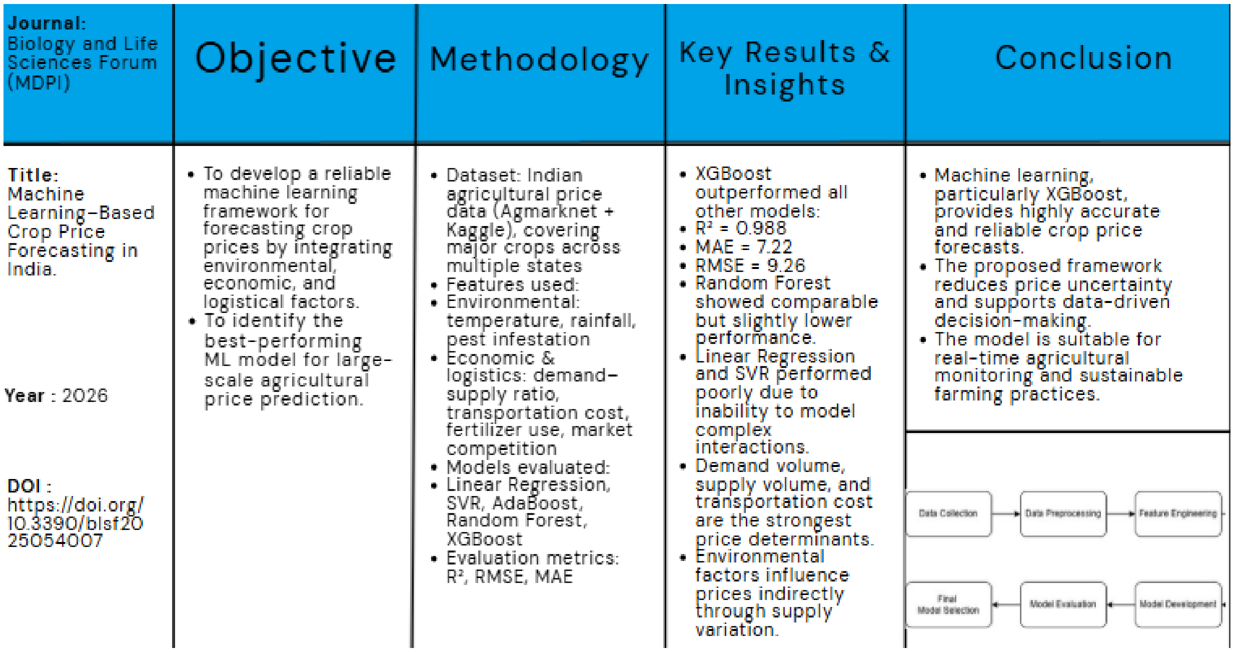
The integration of multi-source data has also been identified as a critical factor in improving prediction models. Inpun and Phrueksawatnon (2025) proposed a machine learning framework that incorporates both historical price data and external influencing variables such as weather conditions and economic indicators. Their findings suggest that multi-source data integration enhances model robustness, reduces uncertainty, and improves forecasting accuracy compared to traditional single-source approaches. A comprehensive literature review conducted by Smith (n.d.) further supports the dominance of machine learning techniques in agricultural price prediction. The review highlights that neural network-based models are the most frequently used due to their ability to model nonlinear relationships effectively. It also notes that commonly used evaluation metrics include RMSE, MAE, and MAPE, and emphasizes the significant influence of climate and market dynamics on agricultural prices.

In addition, the application of deep learning models such as Long Short-Term Memory (LSTM) networks has shown promising results in handling complex and large datasets. A study evaluating multiple models, including ARIMA, SVR, Prophet, XGBoost, and LSTM, found that while ARIMA performs well with smaller datasets, LSTM demonstrates superior scalability and accuracy in multivariate environments. This makes LSTM particularly suitable for real-world applications involving multiple influencing factors and large-scale data (Géron, 2019). Furthermore, recent advancements in hybrid and optimized machine learning techniques have improved long-term forecasting capabilities. Research incorporating reinforcement learning, genetic algorithms, and hybrid models such as GA-ELM and GA-LSTM has demonstrated significant improvements in prediction accuracy and stability. Among these, GA-ELM emerged as the most effective model, outperforming traditional approaches in terms of RMSE, MAE, and MAPE while requiring less training time (Russell & Norvig, 2021). Overall, the literature indicates a clear shift from traditional statistical methods toward advanced AI-driven approaches for agricultural price forecasting. Machine learning and deep learning models, particularly when combined with multi-source data and optimization techniques, offer significant improvements in accuracy, scalability, and robustness. However, challenges such as data availability, model complexity, and computational requirements remain areas for further research.



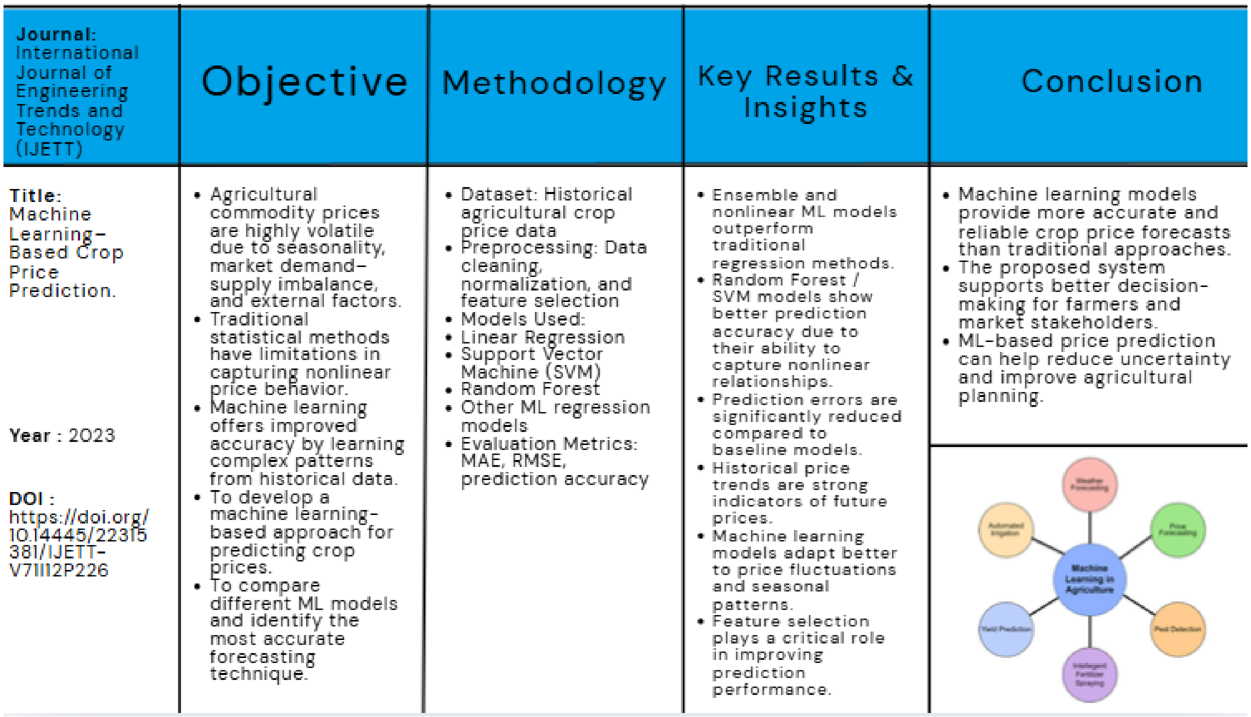
Journal: arXiv	Objective	Methodology	Key Results & Insights	Conclusion
Title: Time-Series Foundation Models for Agricultural Price Forecasting **Year** : 2026 **DOI** : https://doi.org/10.48550/arXiv.2601.06371	• To evaluate whether modern Time-Series Foundation Models (TSFMs) can outperform: • Traditional time-series models • Machine learning models • Deep learning models trained from scratch • USDA's futures-based Season-Average Price (SAP) forecasts	Data: • Monthly commodity prices (corn, soybeans, wheat, cotton) • USDA ERS data from 1997–2025 Models evaluated: 17 models across 4 categories • Traditional (ARIMA, ETS, Naive, Prophet, etc.) • Machine Learning (Random Forest, XGBoost) • Deep Learning (LSTM, N-BEATS, TFT, DeepAR) • Foundation Models (Chronos, Chronos-2, TimesFM 2.5, Time-MoE, Moirai-2) Evaluation: • Monthly price forecasts (up to 12 months ahead) • Marketing Year Average (MYA) price forecasts • Metrics: MAE, RMSE, MAPE • Compared against USDA ERS SAP forecasts	• Time-Series Foundation Models consistently outperform all other models • Zero-shot foundation models (no retraining) beat: • Traditional time-series models • Machine learning models • Deep learning models trained from scratch • Time-MoE achieved the best overall performance: • 54.9% improvement over USDA on wheat • 18.5% improvement over USDA on corn • Deep learning models trained from scratch performed poorly due to limited data • Simple models (Naive) often outperformed complex deep learning models	• Time-Series Foundation Models represent a paradigm shift in agricultural price forecasting • They outperform both traditional statistical methods and USDA futures-based forecasts • TSFMs offer a powerful, scalable solution for economic and agricultural forecasting

Fig. 2: The Literature Review of Time-Series Foundation Models for Agricultural Price Forecasting.



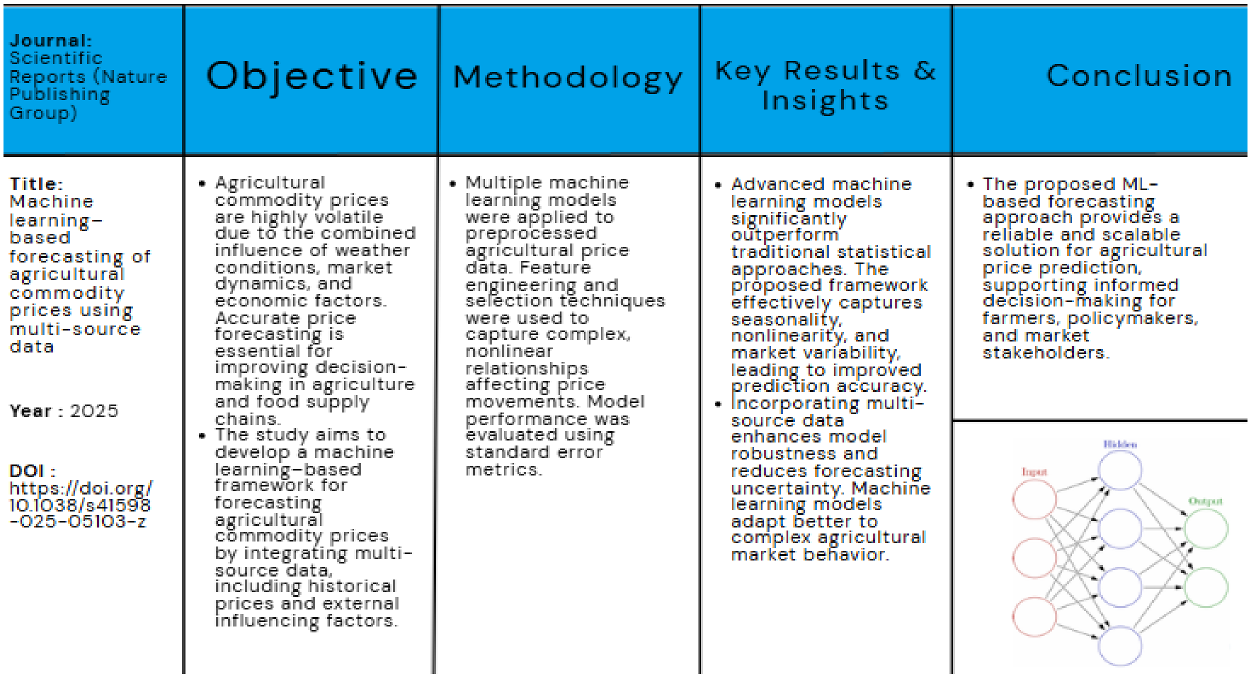
Journal: Biology and Life Sciences Forum (MDPI)	Objective	Methodology	Key Results & Insights	Conclusion
Title: Machine Learning–Based Crop Price Forecasting in India. **Year** : 2026 **DOI** : https://doi.org/10.3390/blsf2025054007	• To develop a reliable machine learning framework for forecasting crop prices by integrating environmental, economic, and logistical factors. • To identify the best-performing ML model for large-scale agricultural price prediction.	• Dataset: Indian agricultural price data (Agmarknet + Kaggle), covering major crops across multiple states • Features used: • Environmental: temperature, rainfall, pest infestation • Economic & logistics: demand–supply ratio, transportation cost, fertilizer use, market competition • Models evaluated: • Linear Regression, SVR, AdaBoost, Random Forest, XGBoost • Evaluation metrics: R², RMSE, MAE	• XGBoost outperformed all other models: • R² = 0.988 • MAE = 7.22 • RMSE = 9.26 • Random Forest showed comparable but slightly lower performance. • Linear Regression and SVR performed poorly due to inability to model complex interactions. • Demand volume, supply volume, and transportation cost are the strongest price determinants. • Environmental factors influence prices indirectly through supply variation.	• Machine learning, particularly XGBoost, provides highly accurate and reliable crop price forecasts. • The proposed framework reduces price uncertainty and supports data-driven decision-making. • The model is suitable for real-time agricultural monitoring and sustainable farming practices.

Fig.3: The Literature Review of Machine Learning–Based Crop Price Forecasting in India



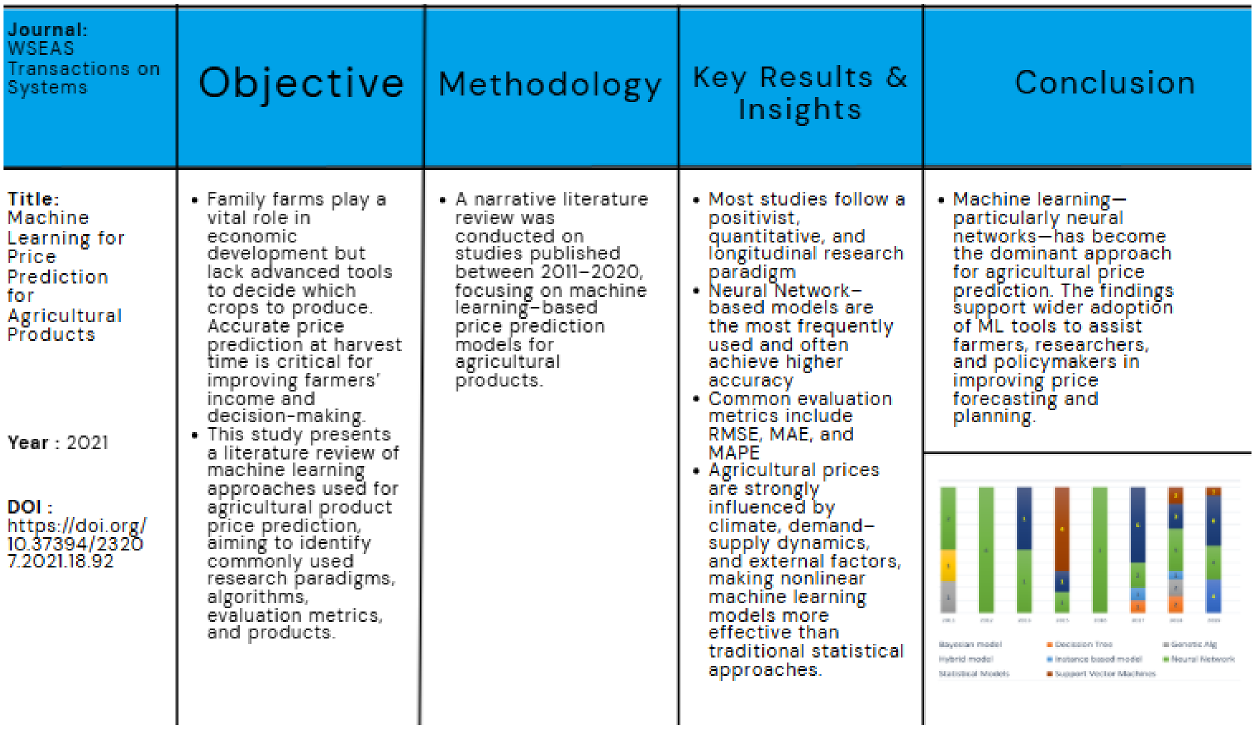
Journal: International Journal of Engineering Trends and Technology (IJETT)	Objective	Methodology	Key Results & Insights	Conclusion
Title: Machine Learning–Based Crop Price Prediction. **Year** : 2023 **DOI** : https://doi.org/10.14445/22315381/IJETT-V71I12P226	• Agricultural commodity prices are highly volatile due to seasonality, market demand–supply imbalance, and external factors. • Traditional statistical methods have limitations in capturing nonlinear price behavior. • Machine learning offers improved accuracy by learning complex patterns from historical data. • To develop a machine learning-based approach for predicting crop prices. • To compare different ML models and identify the most accurate forecasting technique.	• Dataset: Historical agricultural crop price data • Preprocessing: Data cleaning, normalization, and feature selection • Models Used: • Linear Regression • Support Vector Machine (SVM) • Random Forest • Other ML regression models • Evaluation Metrics: MAE, RMSE, prediction accuracy	• Ensemble and nonlinear ML models outperform traditional regression methods. • Random Forest / SVM models show better prediction accuracy due to their ability to capture nonlinear relationships. • Prediction errors are significantly reduced compared to baseline models. • Historical price trends are strong indicators of future prices. • Machine learning models adapt better to price fluctuations and seasonal patterns. • Feature selection plays a critical role in improving prediction performance.	• Machine learning models provide more accurate and reliable crop price forecasts than traditional approaches. • The proposed system supports better decision-making for farmers and market stakeholders. • ML-based price prediction can help reduce uncertainty and improve agricultural planning.

Fig 4: The Literature Review of Machine Learning–Based Crop Price Prediction.



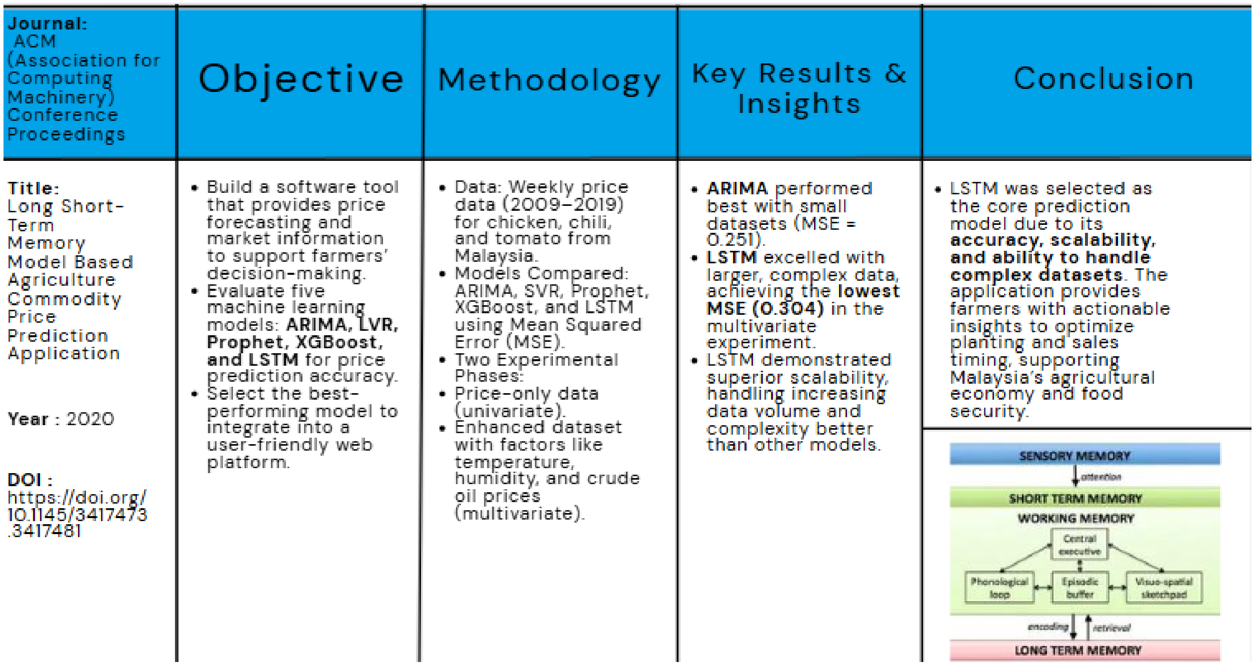
Journal: Scientific Reports (Nature Publishing Group)	Objective	Methodology	Key Results & Insights	Conclusion
Title: Machine learning–based forecasting of agricultural commodity prices using multi-source data **Year** : 2025 **DOI** : https://doi.org/10.1038/s41598-025-05103-z	• Agricultural commodity prices are highly volatile due to the combined influence of weather conditions, market dynamics, and economic factors. Accurate price forecasting is essential for improving decision-making in agriculture and food supply chains. • The study aims to develop a machine learning–based framework for forecasting agricultural commodity prices by integrating multi-source data, including historical prices and external influencing factors.	• Multiple machine learning models were applied to preprocessed agricultural price data. Feature engineering and selection techniques were used to capture complex, nonlinear relationships affecting price movements. Model performance was evaluated using standard error metrics.	• Advanced machine learning models significantly outperform traditional statistical approaches. The proposed framework effectively captures seasonality, nonlinearity, and market variability, leading to improved prediction accuracy. • Incorporating multi-source data enhances model robustness and reduces forecasting uncertainty. Machine learning models adapt better to complex agricultural market behavior.	• The proposed ML-based forecasting approach provides a reliable and scalable solution for agricultural price prediction, supporting informed decision-making for farmers, policymakers, and market stakeholders.

Fig 5: Machine learning–based forecasting of agricultural commodity prices using multi-source data.



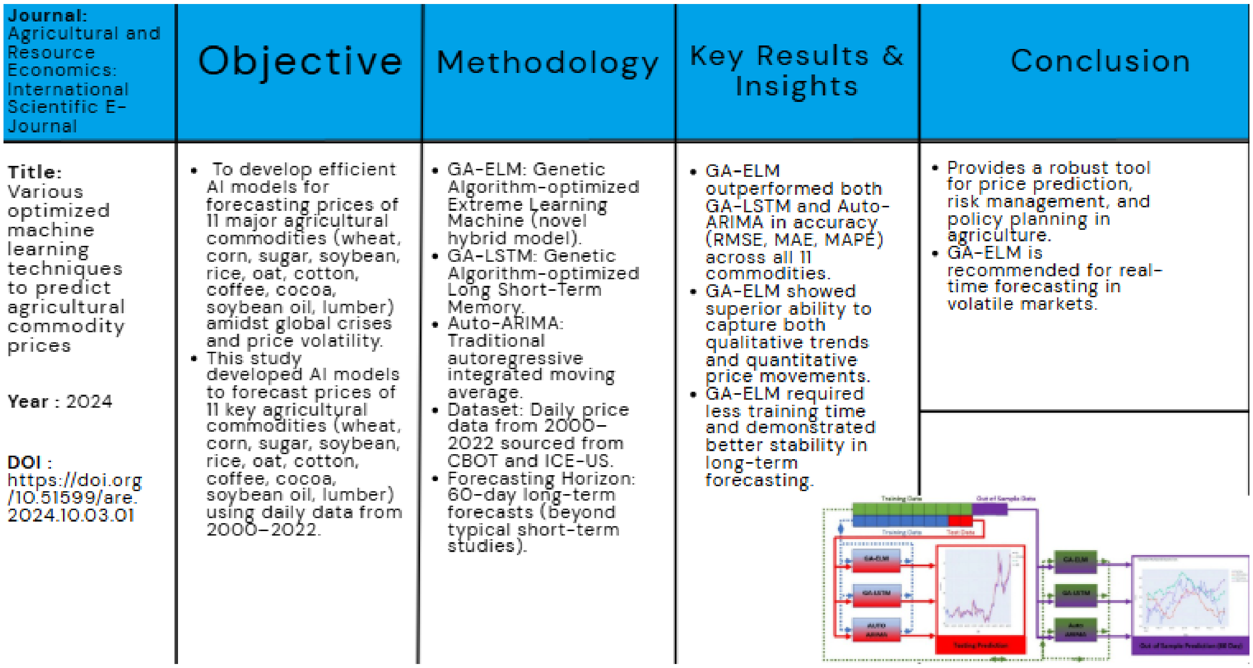
Journal: WSEAS Transactions on Systems	Objective	Methodology	Key Results & Insights	Conclusion
Title: Machine Learning for Price Prediction for Agricultural Products **Year** : 2021 **DOI** : https://doi.org/10.37394/23207.2021.18.92	• Family farms play a vital role in economic development but lack advanced tools to decide which crops to produce. Accurate price prediction at harvest time is critical for improving farmers' income and decision-making. • This study presents a literature review of machine learning approaches used for agricultural product price prediction, aiming to identify commonly used research paradigms, algorithms, evaluation metrics, and products.	• A narrative literature review was conducted on studies published between 2011–2020, focusing on machine learning–based price prediction models for agricultural products.	• Most studies follow a positivist, quantitative, and longitudinal research paradigm • Neural Network–based models are the most frequently used and often achieve higher accuracy • Common evaluation metrics include RMSE, MAE, and MAPE • Agricultural prices are strongly influenced by climate, demand–supply dynamics, and external factors, making nonlinear machine learning models more effective than traditional statistical approaches.	• Machine learning—particularly neural networks—has become the dominant approach for agricultural price prediction. The findings support wider adoption of ML tools to assist farmers, researchers, and policymakers in improving price forecasting and planning.

Fig. 6: Machine Learning for Price Prediction for Agricultural Products.



Journal: ACM (Association for Computing Machinery) Conference Proceedings	Objective	Methodology	Key Results & Insights	Conclusion
Title: Long Short-Term Memory Model Based Agriculture Commodity Price Prediction Application **Year** : 2020 **DOI :** https://doi.org/10.1145/3417473.3417481	• Build a software tool that provides price forecasting and market information to support farmers' decision-making. • Evaluate five machine learning models: **ARIMA, LVR, Prophet, XGBoost, and LSTM** for price prediction accuracy. • Select the best-performing model to integrate into a user-friendly web platform.	• Data: Weekly price data (2009–2019) for chicken, chili, and tomato from Malaysia. • Models Compared: ARIMA, SVR, Prophet, XGBoost, and LSTM using Mean Squared Error (MSE). • Two Experimental Phases: • Price-only data (univariate). • Enhanced dataset with factors like temperature, humidity, and crude oil prices (multivariate).	• **ARIMA** performed best with small datasets (MSE = 0.251). • **LSTM** excelled with larger, complex data, achieving the **lowest MSE (0.304)** in the multivariate experiment. • LSTM demonstrated superior scalability, handling increasing data volume and complexity better than other models.	• LSTM was selected as the core prediction model due to its **accuracy, scalability, and ability to handle complex datasets**. The application provides farmers with actionable insights to optimize planting and sales timing, supporting Malaysia's agricultural economy and food security.

Fig. 7: Long Short-Term Memory Model-Based Agriculture Commodity Price Prediction Application.



Journal: Agricultural and Resource Economics: International Scientific E-Journal	Objective	Methodology	Key Results & Insights	Conclusion
Title: Various optimized machine learning techniques to predict agricultural commodity prices **Year** : 2024 **DOI :** https://doi.org/10.51599/are.2024.10.03.01	• To develop efficient AI models for forecasting prices of 11 major agricultural commodities (wheat, corn, sugar, soybean, rice, oat, cotton, coffee, cocoa, soybean oil, lumber) amidst global crises and price volatility. • This study developed AI models to forecast prices of 11 key agricultural commodities (wheat, corn, sugar, soybean, rice, oat, cotton, coffee, cocoa, soybean oil, lumber) using daily data from 2000–2022.	• GA-ELM: Genetic Algorithm-optimized Extreme Learning Machine (novel hybrid model). • GA-LSTM: Genetic Algorithm-optimized Long Short-Term Memory. • Auto-ARIMA: Traditional autoregressive integrated moving average. • Dataset: Daily price data from 2000–2022 sourced from CBOT and ICE-US. • Forecasting Horizon: 60-day long-term forecasts (beyond typical short-term studies).	• GA-ELM outperformed both GA-LSTM and Auto-ARIMA in accuracy (RMSE, MAE, MAPE) across all 11 commodities. • GA-ELM showed superior ability to capture both qualitative trends and quantitative price movements. • GA-ELM required less training time and demonstrated better stability in long-term forecasting.	• Provides a robust tool for price prediction, risk management, and policy planning in agriculture. • GA-ELM is recommended for real-time forecasting in volatile markets.

Fig.8: The Literature Review of Various optimized machine learning techniques to predict agricultural commodity prices

III. PROPOSED PROJECT FUNCTIONAL MODULES IMPLEMENTATION AND ALGORITHMIC LOGIC

Agri-Predict utilizes a combination of machine learning and deep learning algorithms to enhance predictive accuracy:

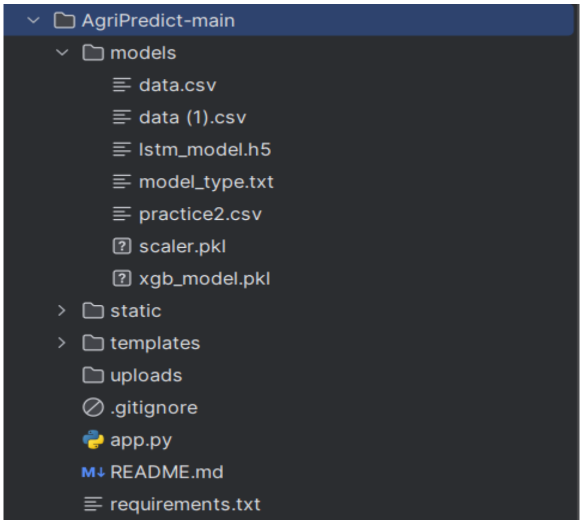
Long Short-Term Memory (LSTM):

A type of Recurrent Neural Network (RNN) designed to analyze sequential time-series data and retain long-term dependencies. Helps capture recurring seasonal price trends in crop commodities over time while avoiding issues like vanishing gradients. The LSTM model processes multi-step input windows of historical prices and outputs weekly or monthly price forecasts, making it particularly effective for identifying multi-season price cycles in crops like wheat, paddy, onion, and tomato.

Sentiment Analysis using NLP:
Natural Language Processing (NLP) techniques are applied to assess the impact of agricultural news, government policy announcements, and social media sentiment on commodity price trends. Uses lexicon-based and machine learning-based sentiment classification models trained on agricultural domain-specific corpora to quantify external market signals.

Extreme Gradient Boosting (XGBoost):
In Agri-Predict, XGBoost is trained on engineered features including market arrival volumes, MSP values, rainfall index, crop season flags, fuel prices, and lagged price variables. It delivers strong baseline predictions with built-in feature importance rankings, enabling transparent identification of the most influential drivers of commodity price movement. XGBoost complements LSTM by excelling in scenarios where structured feature relationships dominate over sequential temporal patterns — particularly effective for shorter prediction windows and sparse data markets.
The development of Agri-Predict involves several functional modules, each serving a critical role in agricultural commodity price forecasting and market intelligence: User Registration and Authentication: Secure sign-up and login functionality for farmers, traders, and analysts. Role-based access control for different user categories. User profile management including preferred crops, markets, and forecast horizons. Agricultural Market Data Processing: Real-time commodity price data integration via AGMARK and state APMC APIs. Historical data ingestion, cleaning, and feature extraction pipeline. Crop Price Prediction Module: Implementation of LSTM for multi-step ahead sequential price prediction (weekly/monthly horizons). Implementation of XGBoost for feature-driven ensemble price prediction with built-in feature importance ranking. Dual-model output comparison allowing users to view LSTM vs XGBoost predictions side-by-side. Exogenous feature integration: rainfall, MSP, season flags, and market arrival data for enhanced accuracy. Market Intelligence and Advisory System: Automated sell/buy timing recommendations based on predicted price trajectories. Commodity comparison across multiple mandis and regions. Analytics & Visualization: Interactive dashboards displaying crop price trends and forecasts. Performance analytics, prediction confidence intervals, and risk assessment tools. Needs Assessment: Conduct surveys and interviews with farmers, commodity traders, mandi officials, and agricultural policymakers to understand their key requirements for a commodity price forecasting platform. Analyze existing agricultural market tools and government portals to identify their limitations and gather insights on desired improvements. Assess challenges faced in price discovery, data access, prediction accuracy, and user experience for diverse agricultural stakeholders. Requirement Definition: Define essential features based on user needs, including real-time mandi price tracking, crop-specific predictive analytics, risk assessment, and automated price alerts. Prioritize critical functionalities such as multi-horizon forecasting (weekly and monthly), secure data access, AI-driven price recommendations, and an intuitive interface for low-literacy users.

IV. AGRI-PREDICT PROTOTYPE, ALGORITHM AND PROGRAM LOGIC:



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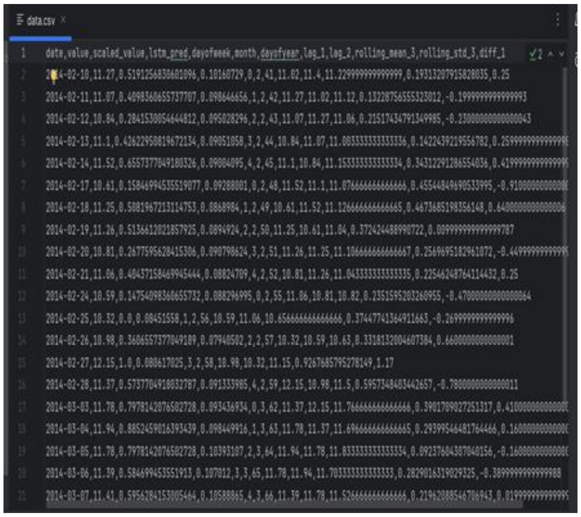

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Fig 9 &10: Project directory and Dataset Agri-Predict: Crop Price Predictor

Fig 11 &12: LSTM model and XGBoost model Agri-Predict: Crop Price Predictor

V. FRONTEND PART AND BACKEND PART DESIGN

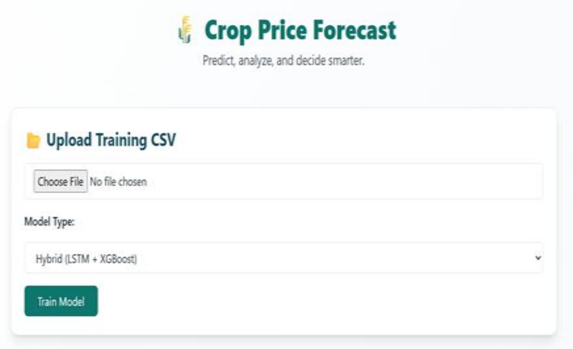
Platform Design: Design an intuitive and user-friendly interface that ensures seamless navigation for farmers and traders with varying levels of digital literacy. Implement real-time commodity price visualization with interactive charts, forecast graphs, and regional market heatmaps. Integrate AI-powered prediction models for enhanced price decision-making at the crop and mandi level. Development: Utilize optimal software and hardware configurations to ensure system scalability, data security, and reliable prediction throughput. Implement machine learning models, Long Short-Term Memory (LSTM) for sequential deep learning-based price forecasting and Extreme Gradient Boosting (XGBoost) for structured feature-driven ensemble prediction, ensuring dual-model coverage for diverse forecasting scenarios. Develop data ingestion pipelines and API connectors for seamless agricultural market data access from AGMARK, IMD, and government databases.

```html
<html lang="en">
<body class="bg-gradient-to-br from-white to-slate-100 min-h-screen text-gray-800">
  <div class="max-w-5xl mx-auto p-6 space-y-12">
    <section class="bg-white shadow-lg rounded-xl p-6 border border-slate-200">
      <div class="overflow-x-auto">
          <thead class="bg-slate-200">
            <tr><th class="px-4 py-2">Date</th><th class="px-4 py-2">Predicted Price</th></tr>
          </thead>
          <tbody>
            {% for date, price in forecast_table %}
            <tr class="border-t">
              <td class="px-4 py-2">{{ date }}</td>
              <td class="px-4 py-2">{{ price | round(2) }}</td>
            </tr>
            {% endfor %}
          </tbody>
        </table>
      </div>
    </section>
```

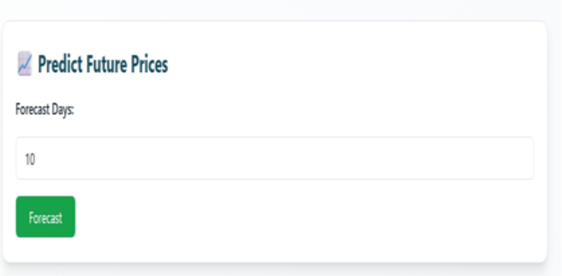
```python
from flask import Flask, request, render_template, send_file
import pandas as pd
import numpy as np
import os
os.environ['TF_ENABLE_ONEDNN_OPTS'] = '0'
import pickle
from datetime import datetime, timedelta
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
import xgboost as xgb
import random

app = Flask(__name__)

UPLOAD_FOLDER = "uploads"
MODEL_FOLDER = "models"
os.makedirs(UPLOAD_FOLDER, exist_ok=True)
os.makedirs(MODEL_FOLDER, exist_ok=True)


DATA_PATH = os.path.join(MODEL_FOLDER, "data.csv")
LSTM_MODEL_PATH = os.path.join(MODEL_FOLDER, "lstm_model.h5")
XGB_MODEL_PATH = os.path.join(MODEL_FOLDER, "xgb_model.pkl")
SCALER_PATH = os.path.join(MODEL_FOLDER, "scaler.pkl")
MODEL_TYPE_PATH = os.path.join(MODEL_FOLDER, "model_type.txt")
```

Fig 13 & 14: HTML code and App.py codes Agri-Predict: Crop Price Predictor

VI. AGRI-PREDICT WEBSITE SCREENSHOTS

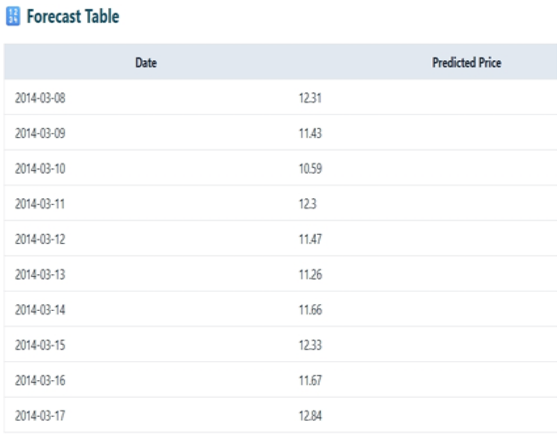


Model Type: Hybrid (LSTM + XGBoost)



Forecast Days: 10

Fig.15 &16: Agri-Predict: Crop Price PredictorAgri-Predict: Crop Price Predictor



Forecast Table

Date	Predicted Price
2014-03-08	12.31
2014-03-09	11.43
2014-03-10	10.59
2014-03-11	12.3
2014-03-12	11.47
2014-03-13	11.26
2014-03-14	11.66
2014-03-15	12.33
2014-03-16	11.67
2014-03-17	12.84

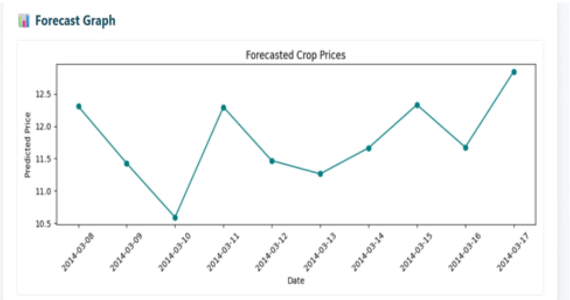


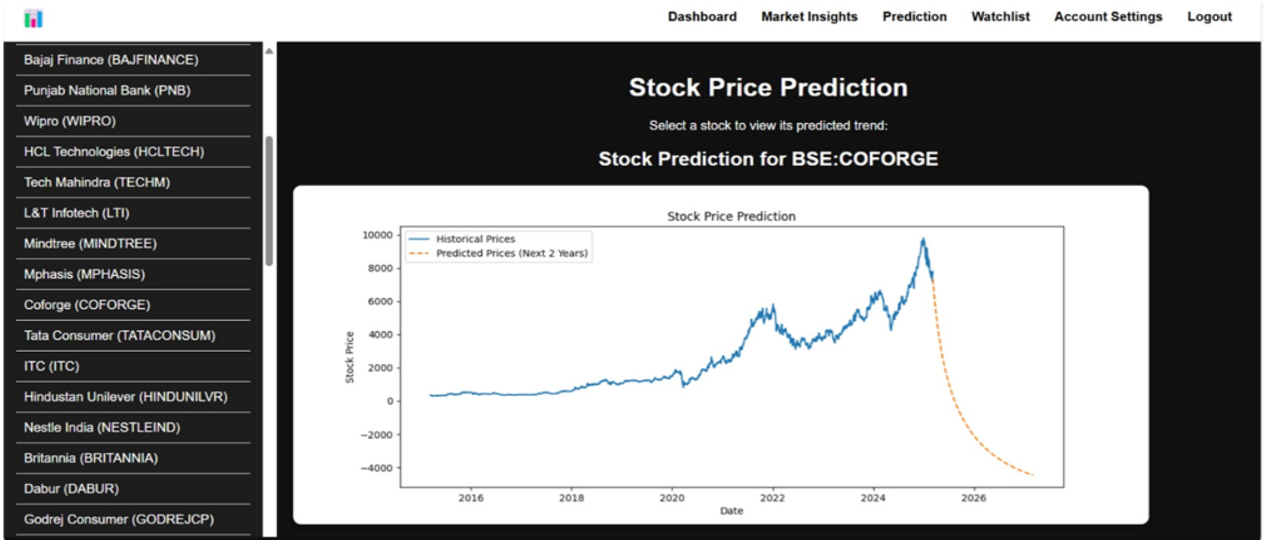
Fig 17 & 18: Agri-Predict: Crop Price Predictor

Summary Recommendation Prices expected to remain stable. Plan accordingly.

Table: Agri-Predict: Crop Price Predictor

Date	Farmer/Seller	Consumer	Government
2014-03-08	Stable prices; act as usual.	Stable market; buy as needed.	Maintain monitoring; no action required.
2014-03-09	Consider selling before price drops further.	Delay buying; prices may go down.	No major action; ensure fair pricing.
2014-03-10	Consider selling before price drops further.	Delay buying; prices may go down.	No major action; ensure fair pricing.
2014-03-11	Hold your crop, price is increasing.	Buy now before prices rise more.	Monitor for inflation; consider price caps.
2014-03-12	Consider selling before price drops further.	Delay buying; prices may go down.	No major action; ensure fair pricing.
2014-03-13	Stable prices; act as usual.	Stable market; buy as needed.	Maintain monitoring; no action required.
2014-03-14	Stable prices; act as usual.	Stable market; buy as needed.	Maintain monitoring; no action required.
2014-03-15	Stable prices; act as usual.	Stable market; buy as needed.	Maintain monitoring; no action required.
2014-03-16	Stable prices; act as usual.	Stable market; buy as needed.	Maintain monitoring; no action required.
2014-03-17	Hold your crop, price is increasing.	Buy now before prices rise more.	Monitor for inflation; consider price caps.

Testing:
Conduct extensive testing, including unit testing, integration testing, and system testing, to identify and resolve issues across prediction and data pipeline modules. Implement back testing of prediction models using multi-year historical commodity price data to evaluate forecasting accuracy and model stability. Gather feedback from early users including farmers and mandi traders to refine platform functionalities and user experience. Deployment: Deploy Agri-Predict to users with proper documentation, user guides, and tutorial materials for easy adoption across different stakeholder groups. Ensure the system is optimized for real-time data updates, low-latency predictions, and secure access across web and mobile interfaces. Monitor user behaviour, prediction accuracy in live market conditions, and collect insights for further platform improvement. Updating and Maintenance: Establish a continuous monitoring and maintenance mechanism to promptly address technical issues, data pipeline failures, and software updates. Regularly retrain AI models with incoming market data to maintain and improve prediction accuracy as commodity market dynamics evolve. Introduce new crop categories, regional market coverage, and enhanced features based on user feedback and evolving agricultural market trends.



Stock Price Prediction

Select a stock to view its predicted trend:

Stock Prediction for BSE:COFORGE

Fig. 19: Agri-Predict: Crop Price Predictor

VII. CONTRIBUTION AND FINDINGS

The Agri-Predict project aims to provide a data-driven, intelligent, and user-friendly agricultural commodity price forecasting platform, enabling farmers, traders, and policymakers to make informed financial and operational decisions. By leveraging a dual-model architecture combining LSTM-based deep learning for sequential price pattern detection and XGBoost-based ensemble learning for structured feature exploitation, real-time market data from government commodity APIs, and domain-enriched feature engineering incorporating climate and policy signals, Agri-Predict enhances forecasting efficiency, minimizes price uncertainty, and improves market planning accuracy across weekly and monthly horizons. The integration of XGBoost further provides transparent, interpretable feature importance scores that reveal which agricultural variables most significantly influence price movements, offering unique explainability alongside LSTM's powerful temporal predictions. This platform serves as a model for integrating AI-driven price intelligence with traditional agricultural market structures, highlighting the transformative importance of hybrid machine learning technology in modern farm-to-market price discovery and agricultural investment strategies.

VIII. CONCLUSION

The Agri-Predict platform presents a comprehensive and intelligent approach to agricultural commodity price forecasting, integrating machine learning, real-time data analysis, and advanced time-series modeling in a robust dual-model architecture. By utilizing Long Short-Term Memory (LSTM) networks for sequential price pattern detection and long-range trend forecasting, Extreme Gradient Boosting (XGBoost) for structured feature-driven ensemble prediction with transparent feature importance, and Natural Language Processing (NLP) for policy and sentiment-based feature extraction, Agri-Predict enhances the accuracy and interpretability of crop price predictions across weekly and monthly horizons. The complementary strengths of LSTM and XGBoost are central to the platform's forecasting robustness — LSTM captures temporal dependencies and seasonal cycles invisible to traditional models, while XGBoost rapidly processes structured exogenous features such as rainfall, MSP, market arrivals, and fuel prices to deliver highly accurate and explainable predictions. Through a user-friendly interface, real-time mandi data tracking, multi-crop and multi-market coverage, and side-by-side model comparison outputs, Agri-Predict empowers agricultural stakeholders with the tools needed to navigate commodity price volatility and optimize procurement, selling, and storage decisions. The project's findings underscore the significance of hybrid AI-driven analytics in agricultural financial decision-making, demonstrating that intelligent multi-model price prediction systems can substantially improve market efficiency and reduce financial risks for smallholder farmers and agribusinesses alike. Moving forward, continuous model retraining with incoming market data, incorporation of satellite-based crop yield forecasts, and integration of more advanced architectures such as Temporal Fusion Transformers will further enhance the platform's effectiveness, positioning Agri-Predict as a powerful and indispensable tool in the dynamic and critical landscape of agricultural commodity markets.

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