

DriftAgri-Net A Drift-Aware Adaptive Deep Learning Framework for Real-Time Agricultural Commodity Price Prediction

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ABSTRACT

Agricultural commodity prices are fluctuates significantly due to seasonal variations, market demand, and economic uncertainties which make accurate price prediction a challenging task. Traditional machine learning models rely on static learning approach that fail to adapt to continuously evolving market conditions. To address this limitation, this study proposes DriftAgri-Net, a drift-aware adaptive deep learning framework for real-time agricultural commodity price prediction. The proposed framework integrates sliding window normalization, concept drift detection, incremental learning, adaptive model tuning, and dynamic ensemble prediction. ADWIN and Page-Hinkley techniques are employed to identify distributional changes in streaming market data. Finally, an adaptive ensemble mechanism dynamically combines Multi-Layer Perceptron (MLP) and Deep Neural Network (DNN) models based on recent prediction performance. The framework was evaluated using agricultural commodity datasets collected from Agricultural Produce Market Committees (APMCs) across India. Experimental results demonstrate that the proposed DriftAgri-Net model outperforms conventional deep learning in terms of accuracy, precision, recall, and F1-score. The proposed framework effectively simulates real-time forecasting conditions for intelligent agricultural decision-support systems, supporting farmers, and supply-chain stakeholders in dynamic market environments.

Keywords: *Agricultural Commodity Price Prediction, Deep Learning, Concept Drift Detection, Agricultural Market Analytics, Adaptive Ensemble Learning*

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1. INTRODUCTION

Agriculture plays a critical role in the economic development and food security of many countries, where a large proportion of the population depends on farming and agricultural trade for their livelihood. Climate unpredictability, seasonal output, transportation limitations, governmental regulations, supply-demand mismatch, and worldwide economic conditions all have a significant impact on agricultural commodity markets [1, 2]. For farmers, traders, policymakers, and supply-chain stakeholders, accurate agricultural commodity price forecast is crucial since these uncertainties frequently result in severe price volatility [3]. Strategic decision-making concerning crop planning, storage management, market regulation, and risk reduction can be aided by dependable forecasting systems. Intelligent forecasting frameworks may greatly increase agricultural market transparency and economic sustainability, according to recent studies [4].

Traditional statistical forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Vector Autoregression (VAR), have been widely used in agricultural price analysis due to their ability to model temporal relationships and volatility patterns. However, these approaches require linearity and stationary in time-series data, limiting their ability to predict complicated nonlinear agricultural market dynamics. Agricultural commodity prices frequently display sudden swings, structural discontinuities, and non-stationary behavior that cannot be successfully recorded by traditional statistical approaches [5-6]. Recent research has reported that traditional forecasting models frequently experience reduced predictive stability under highly volatile agricultural market conditions.

Machine learning and deep learning techniques are being used more often to anticipate agricultural commodity prices in order to get around these restrictions. In

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agricultural datasets, methods like Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transformer-based architectures have shown increased capacity to capture nonlinear patterns and temporal dependencies. For agricultural forecasting applications, recent hybrid deep learning frameworks combining CNN, LSTM, Transformer, and optimization-based algorithms have demonstrated encouraging performance gains [7-8].

Although deep learning approaches improve predictive performance, many existing forecasting systems remain static in nature because they are trained using historical datasets under fixed data distributions. In real-world agricultural environments, commodity price behavior continuously evolves due to changing climatic conditions, market interventions, economic instability, and consumer demand patterns. These evolving characteristics lead to concept drift, where the statistical properties of streaming data change over time, causing previously trained models to gradually lose prediction accuracy. Research on learning under concept drift has highlighted that ignoring distributional changes significantly degrades the reliability and robustness of machine learning systems operating in dynamic environments.

Another major limitation of existing agricultural forecasting frameworks is the insufficient integration of adaptive learning strategies for real-time deployment scenarios. Most current studies focus on offline forecasting using static datasets and do not adequately simulate real-world streaming environments where data continuously arrives and market conditions evolve dynamically. Furthermore, limited research has explored the combined integration of concept drift detection, adaptive ensemble learning, sliding window normalization, and incremental deep learning within a unified agricultural forecasting framework.

To address these research gaps, this study proposes DriftAgri-Net, a drift-aware adaptive deep learning framework for real-time agricultural commodity price prediction. The proposed framework integrates sliding window normalization [9], concept drift detection, adaptive model tuning [10], incremental learning, and dynamic ensemble prediction into a unified architecture. Adaptive Windowing (ADWIN) and the Page-Hinkley [10] test are employed to identify distributional changes in streaming market data, while adaptive ensemble learning dynamically combines Multi-Layer Perceptron (MLP) and Deep Neural Network (DNN) models based on recent prediction performance. The proposed framework is designed to simulate real-time agricultural forecasting conditions using sequential offline data processing, enabling continuous adaptation to evolving market behavior.

The major contributions of this study are summarized as follows:

- Development of a drift-aware adaptive deep learning framework for agricultural commodity price prediction.
- Integration of ADWIN and Page-Hinkley concept drift detection techniques for identifying evolving market patterns.
- Implementation of incremental learning and adaptive model tuning to improve forecasting robustness without complete retraining.
- Introduction of a dynamic ensemble weighting mechanism combining MLP and DNN models for enhanced predictive performance.
- Simulation of real-time agricultural forecasting environments using sequential data processing for practical deployment readiness.

The remainder of this paper is organized as follows. Section 2 presents the literature review and research gaps. Section 3 describes the proposed DriftAgri-Net framework and methodology. Section 4 discusses the experimental results and performance evaluation. Finally, Section 5 concludes the study and outlines future research directions.

2. LITERATURE REVIEW

2.1 Traditional Statistical Approaches for Agricultural Price Prediction

Agricultural commodity price prediction has long been an important research area due to its direct impact on food security, market stability, and economic sustainability. Traditional statistical and econometric models such as Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been extensively applied for analyzing agricultural market trends and commodity price behavior. These approaches are effective in modeling linear temporal relationships and short-term market fluctuations. Several studies reported satisfactory performance of ARIMA-based forecasting models for short-duration agricultural price estimation tasks. However, agricultural markets are highly dynamic and influenced by nonlinear factors including climatic uncertainty, supply-demand imbalance, transportation disruptions, and policy interventions. As a result, conventional statistical methods often fail to accurately capture nonlinear dependencies and rapidly changing market conditions, thereby limiting their predictive reliability in real-world agricultural environments [11], [12].

2.2 Machine Learning-Based Agricultural Price Prediction

To overcome the limitations of statistical approaches, researchers increasingly adopted machine learning techniques for agricultural commodity price prediction. Models such as Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), Gradient Boosting, and Artificial Neural Networks (ANN)

demonstrated improved capability in learning nonlinear patterns from agricultural datasets. Machine learning models can effectively process heterogeneous market information and identify complex feature interactions that are difficult to model using traditional techniques. Recent studies showed that optimized machine learning frameworks significantly improve agricultural price prediction accuracy compared with conventional statistical models [13]. Despite these improvements, many existing machine learning approaches remain static in nature because the models are trained using fixed historical datasets without considering evolving data distributions. Consequently, their performance degrades when market behavior changes over time.

2.3 Deep Learning and Hybrid Intelligent Frameworks

Deep learning approaches have further advanced agricultural market prediction by enabling hierarchical feature learning and improved temporal pattern extraction. Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transformer-based architectures have shown promising results in agricultural commodity analysis. Hybrid deep learning frameworks integrating CNN, LSTM, attention mechanisms, and optimization algorithms have demonstrated superior performance for complex agricultural prediction tasks. Recent Transformer-based agricultural forecasting systems effectively captured long-range temporal dependencies and nonlinear market variations [14]. Similarly, hybrid neural frameworks combining multiple learning models improved robustness and prediction stability under fluctuating market conditions [15].

Although deep learning approaches significantly improve predictive capability, most existing frameworks are still designed under static learning assumptions. These systems generally rely on offline training processes and are unable to dynamically adapt to continuously changing agricultural market environments. In practical scenarios, agricultural commodity prices evolve over time due to seasonal variations, weather changes, inflation, policy modifications, and global economic disturbances. Such evolving environments lead to distributional shifts that reduce the effectiveness of static prediction models.

2.4 Concept Drift and Adaptive Learning in Dynamic Environments

Concept drift refers to the phenomenon where the statistical properties of streaming data change over time, causing previously trained machine learning models to gradually lose predictive effectiveness. In agricultural commodity markets, concept drift frequently occurs because of dynamic environmental and economic factors. Recent research highlighted that adaptive learning systems are essential for maintaining prediction stability in continuously evolving data environments. Drift detection methods such as Adaptive Windowing (ADWIN), Drift Detection Method (DDM), Early Drift Detection Method (EDDM), and Page-Hinkley tests have been widely

applied for detecting distributional changes in streaming data applications.

Adaptive learning and incremental learning strategies enable machine learning models to continuously update their parameters using newly arriving data without complete retraining. Incremental learning frameworks reduce computational complexity while improving scalability for real-time prediction systems. Recent studies demonstrated that combining concept drift detection with adaptive model updating significantly improves prediction robustness in dynamic environments [16]. However, limited research has explored the integration of concept drift detection, adaptive ensemble learning, incremental deep learning, and real-time agricultural market prediction within a unified intelligent framework.

2.5 Research Gaps Identified

Based on the existing literature, several important research gaps remain unresolved in agricultural commodity price prediction systems:

- Most traditional and machine learning-based models assume static data distributions and fail to adapt to evolving agricultural market behavior.
- Existing forecasting frameworks provide limited support for real-time adaptive learning and streaming data environments.
- Concept drift detection techniques are insufficiently explored in agricultural commodity prediction applications.
- Many deep learning models focus only on predictive accuracy while ignoring long-term robustness and adaptability.
- Limited studies integrate adaptive ensemble learning, incremental model updating, and concept drift detection within a unified agricultural intelligence framework.
- Existing systems rarely simulate real-world deployment conditions using sequential real-time data processing.

To address these limitations, this study proposes DriftAgri-Net, a drift-aware adaptive deep learning framework for real-time agricultural commodity price prediction. The proposed framework integrates sliding window normalization, concept drift detection, adaptive model tuning, incremental learning, and dynamic ensemble prediction to improve prediction robustness and adaptability under continuously evolving agricultural market conditions.

3. METHODOLOGY

This study proposes a dynamic and adaptive AI-based forecasting framework designed to predict agricultural commodity prices under evolving market conditions. The framework integrates sliding window normalization, concept drift detection, incremental learning, and an adaptive ensemble learning strategy. The goal of the

proposed methodology is to enable the forecasting system to adapt continuously to changes in data distribution and improve prediction accuracy in real-time scenarios. The overall workflow of the proposed system consists of five major stages: data preprocessing, sliding window

normalization, concept drift detection, adaptive model tuning with incremental learning, and ensemble prediction. The framework simulates a real-time forecasting environment using historical datasets by processing data sequentially.

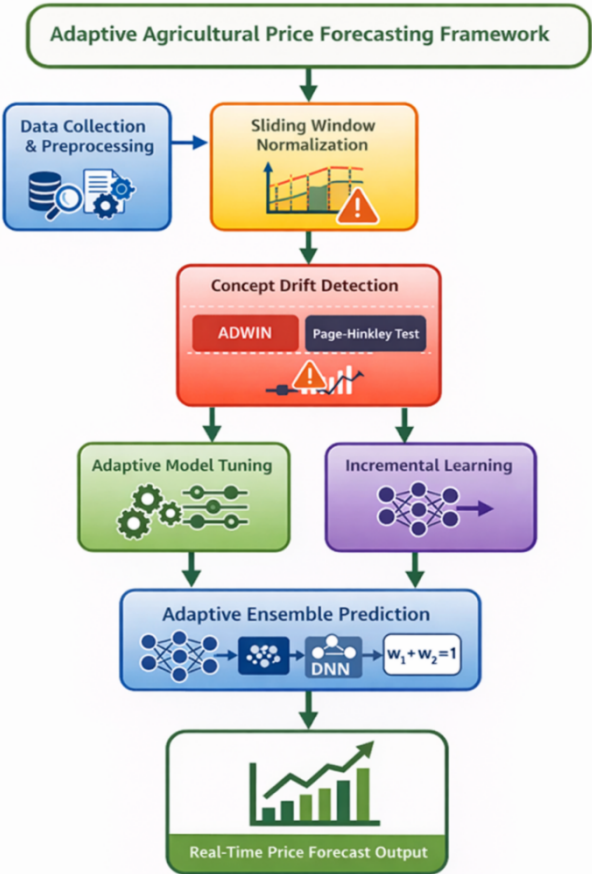


Figure 1. Architecture of the Proposed Drift-Aware Adaptive Forecasting Model

3.1 Dataset

The dataset used in this study is obtained from a publicly available agricultural market data repository provided by the India Data Portal, which publishes daily commodity-wise arrival and price information collected from Agricultural Produce Market Committees (APMCs) across India. Five widely traded vegetables—onion, carrot, brinjal, potato, and tomato—are considered to ensure diversity in price behavior and market dynamics. For each commodity, price data were downloaded separately in comma-separated value (CSV) format, containing attributes such as district, market, commodity group, commodity name, variety, grade, minimum price, maximum price, modal price, price unit, and price date. The individual commodity datasets were subsequently merged into a single unified dataset after schema alignment and data cleaning to facilitate multi-commodity analysis. To enable classification-based price prediction, a target class label was generated using the modal price as the representative market price. A percentile-based thresholding approach was adopted to categorize prices

into three discrete classes: Low, Medium, and High. Specifically, the 33rd and 66th percentiles of the modal price distribution were used as lower and upper thresholds, respectively, ensuring balanced class representation and reducing bias toward extreme price ranges. Prices below the lower threshold were labeled as Low, values between the thresholds as Medium, and those above the upper threshold as High. This labeling strategy provides a robust and data-driven mechanism for transforming continuous price values into meaningful price-range categories suitable for supervised classification models.

3.2 Data Preprocessing

Data preprocessing is essential for developing effective forecasting models using agricultural commodity price data, which often contain inconsistencies and missing values. This study employs techniques to enhance data quality, such as removing or interpolating missing values, identifying and addressing outliers through statistical methods, and transforming data into a structured format suitable for time-series analysis. Feature engineering is applied to capture temporal dependencies, while

normalization is utilized to ensure comparable scales for machine learning algorithms. Finally, the dataset is chronologically divided into training and testing segments to accurately simulate forecasting conditions. These preprocessing steps create a clean and consistent dataset ready for advanced forecasting methods.

3.3 Sliding Window Normalization

Prices for agricultural commodities frequently display non-stationary features, in which the data's statistical characteristics fluctuate over time. Conventional normalization methods rely on global statistics calculated from the complete dataset, which could not accurately represent current market trends. A sliding window normalization approach is used to overcome this restriction. This method uses a fixed-size moving window for data normalization, which is updated continually as new data is received. This enables the model to adjust to current market conditions and regional trends. Let X_t represent the commodity price at time t . The normalized value within a window is computed as:

$$X'_t = \frac{X_t - \mu_w}{\sigma_w} \quad (1)$$

Where X'_t denotes the normalized value, μ_w mean of the values within the current window, σ_w standard deviation within the window. Feature scaling is guaranteed to dynamically adapt to changing data patterns thanks to its localized normalization.

3.4 Concept Drift Detection

Agricultural commodity prices are impacted by unforeseen occurrences in real-world market conditions, including changes in the climate, shifts in policy, and shifts in the world economy. Concept drift, in which the underlying statistical distribution of the data changes over time, might result from these modifications. Two drift detection methods are used to find such changes:

A. ADWIN (Adaptive Windowing)

One popular approach for identifying idea drift in data streams is Adaptive Windowing (ADWIN). It is especially made for settings where the data's statistical characteristics fluctuate over time. Market circumstances often alter in the context of agricultural commodity price forecasting because of things like changes in the environment, supply and demand imbalances, governmental regulations, and shifts in the world economy. The underlying data distribution is altered as a result of these changing patterns, which can seriously impair the performance of static machine learning models. In order to detect such changes and initiate model updates, an adaptive drift detection technique is necessary.

ADWIN works by keeping a sliding window of recently seen data points that is dynamically enlarged. ADWIN automatically modifies the window size based on statistical tests that compare the distributions of two subwindows, in contrast to fixed window techniques. The method eliminates the older part of the window and thinks that a concept drift has happened when a substantial

difference between the statistical characteristics of the two segments is found.

Let the data stream be represented as a sequence of observations:

$$X = \{x_1, x_2, x_3, \dots, x_t\} \quad (2)$$

where x_t represents the value observed at time t . ADWIN maintains a window w that contains the most recent observations from the stream. At each time step, the window w is divided into two subwindows:

$$w = w_0 \cup w_1 \quad (3)$$

w_0 represents the older portion of the window.

w_1 represents the more recent portion of the window

$$\mu_0 = \frac{1}{|w_0|} \sum_{x \in w_0} x \quad (4)$$

$$\mu_1 = \frac{1}{|w_1|} \sum_{x \in w_1} x \quad (5)$$

μ_0 mean of the first subwindow, μ_1 mean of the second subwindow, $|w_0|$ and $|w_1|$ represent the number of elements in each window. The difference between the means of the two subwindows is calculated as:

$$|\mu_0 - \mu_1| \quad (6)$$

If this difference exceeds a statistically significant threshold, the algorithm concludes that a concept drift has occurred. The threshold value is derived using the Hoeffding inequality, which provides a bound on the probability that the difference between the observed mean and the true mean exceeds a certain value. The drift detection condition is defined as:

$$|\mu_0 - \mu_1| > \epsilon \quad (7)$$

where the threshold ϵ is computed as:

$$\epsilon = \sqrt{\frac{1}{2m} \ln \left(\frac{4}{\delta} \right)} \quad (8)$$

m harmonic mean of the window sizes, δ confidence parameter controlling the false alarm probability. The harmonic mean m is calculated as:

$$m = \frac{1}{\frac{1}{|w_0|} + \frac{1}{|w_1|}} \quad (9)$$

ADWIN detects significant changes in data distribution by discarding older data and updating to more recent information, allowing for a focus on relevant patterns. The algorithm adjusts its window size based on data stability; it enlarges during stable periods to use more historical data and shrinks when changes occur for quicker adaptation. Within a forecasting framework, ADWIN monitors prediction error, triggering adaptive model tuning when drifts are detected, thus maintaining accurate predictions in fluctuating agricultural markets. Its integration ensures

effective detection of changes in commodity price data and responsiveness to market dynamics.

B. Page-Hinkley Test

The Page-Hinkley test is another statistical method used to detect abrupt changes in the mean of a data stream. It calculates the cumulative deviation of observed values from their mean. A drift is detected when the cumulative deviation exceeds a predefined threshold. The Page-Hinkley statistic is defined as:

$$PH_t = \sum_{i=1}^t (x_i - \bar{x} - \delta) \quad (10)$$

x_i denotes the observed value, $\bar{x}$ symbolize mean of observations, δ tolerance parameter. If PH_t exceeds a predefined threshold, the system identifies a distributional change and triggers model adaptation.

C. Adaptive Model Tuning

Adaptive Model Tuning

In dynamic environments such as agricultural commodity markets, the statistical properties of data evolve over time due to external factors including climate variations, seasonal trends, policy interventions, and global economic fluctuations. These changes often lead to concept drift, which can significantly degrade the performance of machine learning models trained on historical data. Therefore, it is essential to incorporate an adaptive mechanism that dynamically updates model parameters in response to detected changes.

In this study, an adaptive model tuning strategy is proposed to automatically adjust model parameters based on real-time data characteristics and prediction performance. The tuning process is triggered whenever concept drift is detected using ADWIN or the Page-Hinkley test. Instead of retraining the model from scratch, the system selectively updates model parameters to ensure rapid adaptation while maintaining computational efficiency. The adaptive tuning process relies on continuous monitoring of model performance. At each time step t , the prediction error is calculated as:

$$e_t = y_t - \hat{y}_t$$

y_t denotes actual commodity price at time t and $\hat{y}_t$ predicted price at time t . To evaluate recent performance trends, a moving average of the error is computed:

$$E_t = \frac{1}{n} \sum_{i=t-n+1}^t |e_i| \quad (11)$$

where n represents the size of the evaluation window. If the error exceeds a predefined threshold or shows a consistent increasing trend, it indicates model degradation, prompting parameter tuning.

Incremental Learning

Traditional machine learning models rely on batch training using static datasets. However, this approach is inefficient

for real-time systems where data arrives continuously. To address this limitation, incremental learning is incorporated into the framework. Incremental learning enables the model to update its parameters using newly arriving data without retraining from scratch.

The benefits of incremental learning include:

- Reduced computational cost
- Faster model adaptation
- Improved scalability for streaming environments

Each time new data becomes available, the model updates its parameters while retaining knowledge from previous observations.

Adaptive Ensemble Prediction

To enhance forecasting accuracy and robustness in dynamic agricultural markets, this study employs an adaptive ensemble prediction strategy that combines multiple machine learning models. Ensemble learning leverages the strengths of individual models while mitigating their weaknesses, leading to improved generalization performance. However, in non-stationary environments, the predictive performance of individual models may vary over time due to concept drift. Therefore, instead of using fixed weights, the proposed framework adopts a dynamic weighting mechanism that continuously adjusts model contributions based on recent performance.

The ensemble consists of two complementary models:

- Multi-Layer Perceptron (MLP): Capable of capturing nonlinear relationships and complex temporal patterns.
- Deep Neural Network (DNN): Effective in learning hierarchical feature representations and modeling complex data distributions.

Let the predictions generated by the individual models at time t be:

$$P_{MLP}(t), P_{DNN}(t) \quad (12)$$

The final ensemble prediction is computed as a weighted combination:

$$P_{final}(t) = w_1(t)P_{MLP}(t) + w_2(t)P_{DNN}(t) \quad (13)$$

$$w_1(t) + w_2(t) = 1 \quad (14)$$

$w_1(t) + w_2(t)$ are the adaptive weights assigned to MLP and DNN, respectively, $P_{final}(t)$ is the final predicted commodity price. The weights are updated dynamically based on the recent prediction errors of each model. Let the prediction errors be defined as:

$$e_{MLP}(t) = |y_t - P_{MLP}(t)| \quad (15)$$

$$e_{DNN}(t) = |y_t - P_{DNN}(t)| \quad (16)$$

To ensure stability, a moving average error over a window of size n is computed:

$$E_{MLP}(t) = \frac{1}{n} \sum_{i=t-n+1}^t |e_{MLP}(i)| \quad (17)$$

$$E_{DNN}(t) = \frac{1}{n} \sum_{i=t-n+1}^t |e_{DNN}(i)| \quad (18)$$

$$w_2(t) = \frac{1/E_{DNN}(t)}{\left(1/E_{MLP}(t)\right) + \left(1/E_{DNN}(t)\right)} \quad (20)$$

The weights are then assigned inversely proportional to the errors:

$$w_1(t) = \frac{1/E_{MLP}(t)}{\left(1/E_{MLP}(t)\right) + \left(1/E_{DNN}(t)\right)} \quad (19)$$

Algorithm 1: Proposed Adaptive AI-Based Framework for Real-Time Agricultural Commodity Price Forecasting

Input: data stream $X = \{x_1, x_2, \dots, x_t\}$

Output: Predicted price $P_{final}(t)$

FOR each time step $t = 1$ to T DO

Step 1: Data Acquisition

Receive new data point x_t

Step 2: Preprocessing

Handle missing values and outliers

Apply sliding window normalization on current window W

Step 3: Feature Preparation

Generate lag features and moving averages

Step 4: Model Prediction

Predict using MLP:

$P_MLP(t) \leftarrow MLP(x_t)$

Predict using DNN:

$P_DNN(t) \leftarrow DNN(x_t)$

Step 5: Ensemble Prediction

Compute final prediction:

$P_final(t) \leftarrow w_1 * P_MLP(t) + w_2 * P_DNN(t)$

Step 6: Error Computation

$$e_MLP(t) \leftarrow |y_t - P_MLP(t)|$$

$$e_DNN(t) \leftarrow |y_t - P_DNN(t)|$$

Step 7: Update Error Buffers

Store recent errors for moving average calculation

Step 8: Concept Drift Detection

Apply ADWIN on error stream

Apply Page-Hinkley test on error stream

IF drift detected THEN

$$D_t \leftarrow 1$$

ELSE

$$D_t \leftarrow 0$$

ENDIF

Step 9: Adaptive Model Tuning

IF $D_t = 1$ THEN

Update MLP parameters:

Adjust learning rate η

Update regularization λ

Update DNN parameters:

Adjust kernel parameter γ

ENDIF

Step 10: Incremental Learning

Update MLP model with new data x_t

Update DNN model incrementally

Step 11: Adaptive Weight Update

Compute moving average errors:

$$E_MLP(t), E_DNN(t)$$

Update weights:

$$w1 \leftarrow (1 / E_MLP) / [(1 / E_MLP) + (1 / E_DNN)]$$

$$w2 \leftarrow (1 / E_DNN) / [(1 / E_MLP) + (1 / E_DNN)]$$

Normalize:

$$w1 + w2 = 1$$

```
Step 12: Output
Store or display final prediction P_final(t)

END FOR
```

4. RESULTS AND DISCUSSION

The experiments were conducted using the agricultural market dataset. The dataset was split into training and testing sets in an 80:20 ratio using stratified sampling to maintain class balance. Prior to model training, categorical variables were translated using appropriate encoding techniques, and numerical characteristics were standardized to achieve consistent scaling across all

inputs. The models were created using standard machine learning frameworks, and all tests were carried out in the same environment to provide a fair comparison. For the proposed strategy, the MLP was used as a feature extractor, and the resulting representations were input into the DNN classifier. Accuracy, precision, recall, and F1-score were used to evaluate model performance in order to provide a comprehensive assessment of categorization efficacy.

Table 1: Performance Comparison of Classification Models

Methods	Accuracy	Precision	Recall	F1 score
SVM	90.18	90.35	90.18	90.11
Random Forest	92.67	92.81	92.67	92.63
Gradient Boosting	91.44	91.57	91.44	91.39
KNN	89.76	89.91	89.76	89.72
MLP	93.12	93.25	93.12	93.08
DNN	94.26	94.41	94.26	94.22
MLP DNN (Proposed)	98.98	98.54	98.63	98.98

The table displays the relative effectiveness of several deep learning and machine learning models for predicting commodities prices. Four commonly used performance metrics—accuracy, precision, recall, and F1-score—are used to assess the models. With the greatest accuracy of 98.98% and outstanding Precision (98.54%), Recall (98.63%), and F1-score (98.98%), the suggested MLP_DNN hybrid model exhibits exceptional prediction abilities. These findings show that using a hybrid learning architecture, the combination of MLP and DNN successfully captures intricate nonlinear patterns and improves classification performance.

With an accuracy of 94.26%, the solo DNN outperforms the benchmark models, closely followed by the MLP with 93.12%. While Gradient Boosting and SVM obtain accuracies of 91.44% and 90.18%, respectively, Random Forest also demonstrates good predictive ability with an accuracy of 92.67%. With an accuracy of 89.76%, KNN performs the worst out of all the models that were assessed. The suggested MLP DNN model consistently outperforms both individual deep learning architectures and traditional machine learning approaches, demonstrating its efficacy in raising the accuracy and dependability of commodity price prediction.

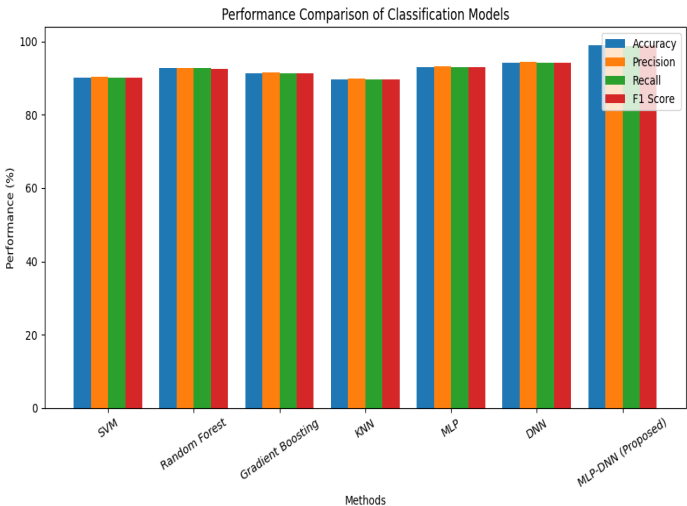


Figure 2. Performance comparison of proposed model MLP-DNN
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Table 2: Performance Comparison of Classification Models

Methods	RMSE	MAE	MAPE	R ²
SVM	6.84	5.41	12.36	0.904
Random Forest	5.72	4.63	10.42	0.926
Gradient Boosting	6.08	4.91	10.98	0.918
KNN	7.26	5.82	13.08	0.891
MLP	5.31	4.26	9.84	0.935
DNN	4.82	3.91	8.95	0.947
MLP_DNN (Proposed)	2.18	1.74	3.52	0.989

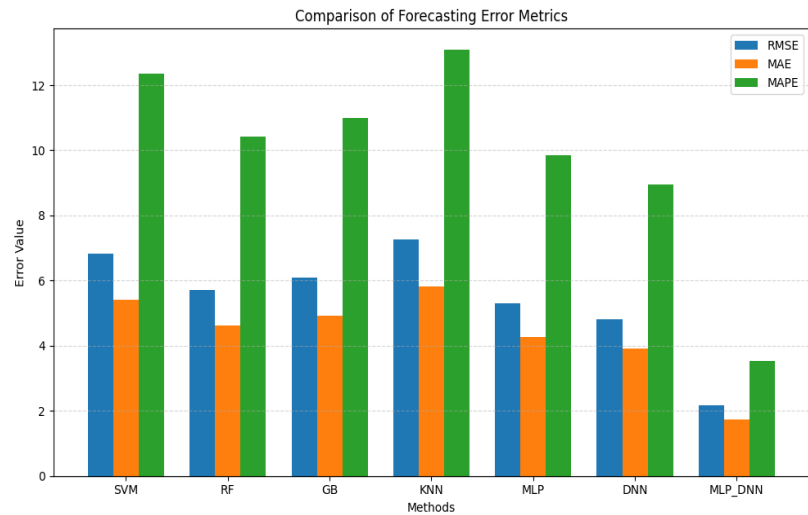


Figure 3. Error metrics comparison with RMSE, MSE and MAPE

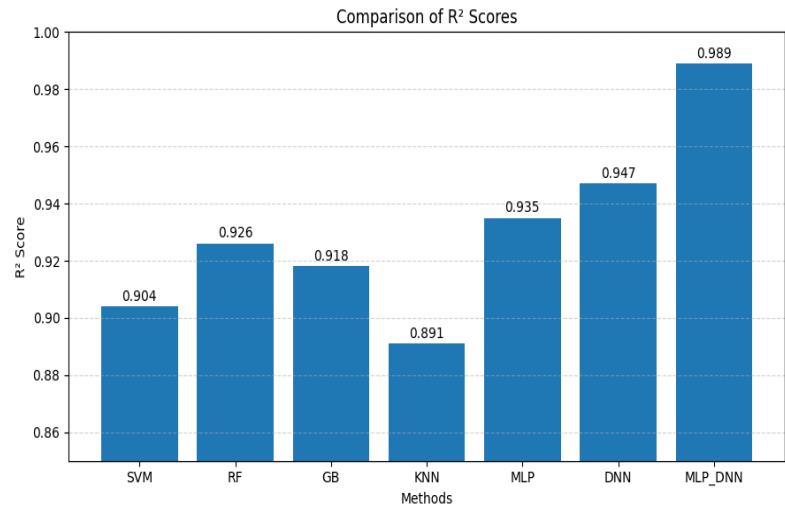


Figure 4 Comparison of **R²** scores among different methods

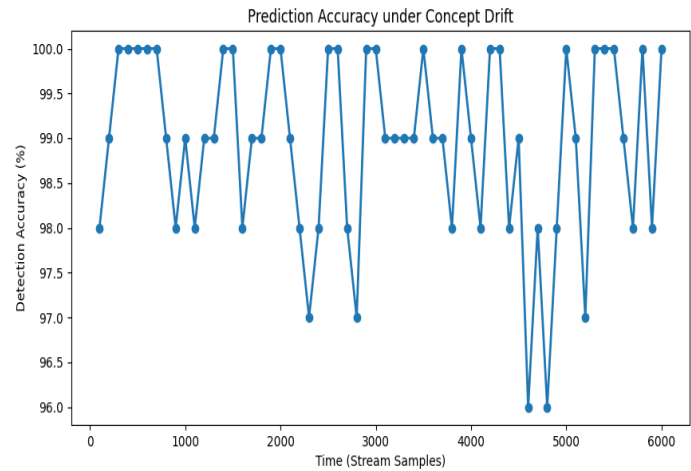


Figure 5 Prediction accuracy under concept drift

Table 2 and Figures 4 and 5 shows the performance evaluation of the proposed DriftAgri-Net framework using forecasting error metrics and prediction accuracy under concept drift. The comparative analysis demonstrates that the proposed MLP_DNN model achieves the lowest RMSE, MAE, and MAPE values along with the highest R^2 score, indicating superior forecasting accuracy and reliability compared to the baseline machine learning and deep learning models. The graphical representation further confirms the reduction in prediction errors and the improvement in model performance. Moreover, the prediction accuracy under concept drift remains consistently high, ranging between 96% and 100%, with only minor fluctuations during changes in data distribution. The adaptive learning mechanism effectively maintains stable prediction performance by continuously adapting to evolving agricultural market conditions, thereby demonstrating the robustness and effectiveness of the proposed framework.

4.1 DISCUSSION OF FINDINGS

The superior performance of the proposed DriftAgri-Net framework can be attributed to its hybrid deep learning architecture and adaptive learning strategy, which collaboratively enhance prediction performance under dynamic agricultural market conditions. By integrating MLP and DNN through a dynamic ensemble mechanism, the framework effectively captures both low-level and high-level feature representations, enabling more robust learning than individual models. The comparative results demonstrate that the proposed model achieves the highest prediction accuracy while simultaneously producing the lowest RMSE, MAE, and MAPE values and the highest R^2 score among all the evaluated methods, indicating its ability to generate reliable and accurate predictions with minimal forecasting error. Furthermore, the prediction accuracy under concept drift remains consistently high throughout the sequential data stream, with only minor performance fluctuations during changes in data distribution. The incorporation of concept drift detection, adaptive model weighting, and incremental learning enables the framework to rapidly adapt to evolving market conditions, thereby maintaining stable prediction

performance and improving model robustness. Overall, these findings demonstrate that the proposed framework provides a more effective and reliable solution for agricultural commodity price prediction than conventional machine learning and standalone deep learning approaches.

PRACTICAL IMPLICATIONS

The proposed model has several important implications for real-world agricultural systems:

- **For Farmers:**
Accurate price-range forecasting enables better decision-making regarding harvest timing, storage, and selling strategies, ultimately improving profitability.
- **For Policy Makers:**
The framework can serve as a decision-support tool for monitoring market trends and identifying potential price fluctuations, allowing timely interventions to ensure market stability and food security.
- **For Supply Chain Stakeholders:**
Traders and distributors can utilize the model for demand planning and inventory optimization, reducing uncertainty and operational risks.

5. CONCLUSION

A dynamic and adaptable AI-based system for real-time agricultural commodity price forecasting was presented in this study. To address the non-stationary nature of agricultural market data, the system incorporates Deep Neural Network (DNN) and Multi-Layer Perceptron (MLP) models inside an adaptive ensemble method, assisted by idea drift detection algorithms. The experimental findings show that the suggested hybrid model performs noticeably better than both independent deep learning models and conventional machine learning models like SVM, Random Forest, Gradient Boosting, and KNN. The model's efficacy was demonstrated by its consistently high precision, recall, and F1-score, as well as its accuracy of 98.98%. The adaptive weighting technique, which dynamically modifies each model's contribution based on recent performance, is the main advantage of the

suggested architecture. This makes it possible for the system to continue having high forecast accuracy even in the face of shifting market conditions. Additionally, by enabling prompt model updates when notable shifts in the data distribution are identified, the integration of drift detection approaches improves resilience. All things considered, the suggested MLP–DNN adaptive ensemble architecture offers a dependable, scalable, and high-performance solution for agricultural commodity price prediction, with great potential for practical implementation. Although the proposed model achieves high accuracy, several directions can be explored to further enhance its performance and applicability: Future work can integrate additional real-world variables such as weather conditions, demand-supply indicators, inflation rates, and government policies, which significantly influence agricultural prices. Implementing the model in a real-time decision support system or web-based platform can enhance its practical usability in agricultural markets.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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