Hybrid TCN-MLP-Attention Network with Bidirectional LSTM for Agricultural Price Prediction

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Abstract: Agricultural market price prediction plays an essential role in supporting supply chain management, market planning, and economic decision-making. However, traditional statistical and machine learning models often struggle to capture complex nonlinear relationships and long-term temporal dependencies present in agricultural price data. To address these limitations, this study proposes an enhanced hybrid deep learning architecture that integrates a Temporal Convolutional Network (TCN), Multilayer Perceptron (MLP), Attention mechanism, and Bidirectional Long Short-Term Memory (BiLSTM) network for time-series price prediction. The TCN module captures multi-scale temporal dependencies using causal and dilated convolutions, while the MLP module performs nonlinear feature transformation. The Attention mechanism highlights important temporal features that significantly influence price trends. Furthermore, the incorporation of the Bidirectional LSTM enables the model to learn contextual information from both past and future sequences, improving feature representation and forecasting accuracy. The model is evaluated using the “U.S. Avocado Market (2015–2023)” dataset obtained from Kaggle. Experimental results demonstrate that the proposed hybrid architecture significantly outperforms conventional models such as SVM, XGBoost, and standard LSTM. The enhanced model achieves an improved R^2 score of 0.9748 with reduced RMSE, confirming its effectiveness and robustness for agricultural time-series price prediction.

***Index terms** - Agricultural price prediction, deep learning, temporal convolutional network (TCN), multilayer perceptron (MLP), attention mechanism, bidirectional LSTM, time-series forecasting.t*

1. INTRODUCTION

With the rapid advancement of global economic integration and digital technologies, accurate prediction of agricultural market prices has become increasingly important for supply chain management, food security, and economic planning. Agricultural commodities are highly sensitive to several dynamic factors such as weather conditions, seasonal production cycles, market demand–supply variations, and international trade policies. These factors create complex nonlinear patterns and temporal dependencies in price data, making agricultural price forecasting a challenging task. Reliable prediction models are essential for farmers, traders, policymakers, and supply chain managers to make informed decisions and minimize economic risks in volatile market environments.

Traditional forecasting approaches, including statistical models such as ARIMA, SARIMA, and exponential smoothing, rely heavily on linear assumptions and stationary data patterns. Although these models perform reasonably well on simple datasets, they often fail to capture the complex nonlinear relationships and long-term temporal dependencies present in agricultural market data. Machine learning approaches such as Support Vector

Machines, Random Forest, and Gradient Boosting methods have improved prediction capabilities; however, they still struggle with large-scale time series data and dynamic feature interactions.

Recent developments in deep learning have introduced powerful techniques for modeling complex temporal patterns in time series data. Architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated significant potential in capturing nonlinear relationships and sequential dependencies. Temporal Convolutional Networks (TCN) further enhance time series modeling through causal and dilated convolutions, allowing the network to learn long-range temporal dependencies efficiently. In addition, attention mechanisms enable models to focus on the most relevant time steps and features, improving interpretability and prediction performance.

To overcome the limitations of existing models, this research proposes an enhanced hybrid deep learning architecture that integrates Temporal Convolutional Network (TCN), Multilayer Perceptron (MLP), Attention mechanism, and Bidirectional Long Short-Term Memory (BiLSTM). The TCN module is responsible for extracting multi-scale temporal features, while the MLP layer performs nonlinear feature transformations to improve representation learning. The attention mechanism identifies critical time steps that significantly influence price fluctuations. Furthermore, the incorporation of a Bidirectional LSTM layer enables the model to process sequential data from both forward and backward directions, allowing it to capture contextual information from past and future time steps simultaneously.

The proposed hybrid architecture is evaluated using the U.S. Avocado Market (2015–2023) dataset obtained from Kaggle, which contains regional price information and temporal attributes. By combining the strengths of TCN, MLP, Attention, and Bidirectional LSTM, the proposed system aims to achieve higher prediction accuracy, improved feature extraction, and better adaptability to dynamic agricultural market conditions. The experimental results demonstrate that the extended hybrid architecture significantly improves forecasting performance and provides a robust solution for agricultural price trend prediction.

2. LITERATURE SURVEY

1. Avocado Price Prediction Using a Hybrid Deep Learning Model: TCN-MLP-Attention Architecture

Forecasting agricultural product prices has grown more crucial due to the rising demand for healthful meals. As a high-value crop, Hass avocados show complicated price swings that are impacted by weather, seasonality, and geography. When dealing with extremely nonlinear and dynamic data, traditional prediction models frequently fail. In order to overcome this, we suggest a hybrid deep learning model called TCN-MLP-Attention Architecture, which combines an attention mechanism for dynamic feature weighting, Multi-Layer Perceptrons (MLP) for nonlinear interactions, and Temporal Convolutional Networks (TCN) for sequential feature extraction. The information, which was gathered via point-of-sale systems and the Hass Avocado Board, includes more than 50,000 records of Hass avocado sales in the United States between 2015 and 2018. It includes factors like sales volume, average price, time, area, weather, and variety type. The suggested model was trained and assessed following methodical preprocessing, which included feature normalization and missing value imputation. With an RMSE of 1.23 and an MSE of 1.51, experimental data show that the TCN-MLP-Attention model outperforms conventional techniques in terms of prediction performance. In addition to offering useful insights for intelligent supply chain management and pricing strategy optimization, this study presents a scalable and efficient method for time series forecasting in agricultural markets.

2. Enhancing Time Series Product Demand Forecasting With Hybrid Attention-Based Deep Learning Models:

In many different sectors, time series forecasting is essential, especially when it comes to anticipating product demand for efficient supply chain management. By utilizing cutting-edge deep learning techniques, this research offers a unique method for time series forecasting. It focuses on hybrid models that integrate attention processes with conventional recurrent neural networks. Our suggested technique, the Hybrid Attention-based Long Short-Term Memory (HA-LSTM) network, combines LSTM layers with multi-head self-attention modules to extract local temporal patterns and long-term relationships from time series data. We demonstrate our model's efficacy in managing intricate, real-world time series with several seasonalities and trends by testing it on a sizable retail dataset from the "Predict Future Sales" competition. According to experimental data, the HA-LSTM achieves a 15% increase in Mean Absolute Percentage Error (MAPE) and a 12% decrease in Root Mean Square Error (RMSE), outperforming cutting-edge baselines like as ARIMA, Prophet, and vanilla LSTM models. Additionally, we do a comprehensive ablation research to examine each component's contribution in our hybrid model. In addition to improving predicting accuracy, the suggested method offers comprehensible attention weights that provide light on the relative significance of various time stages. This study adds to the expanding corpus of research on deep learning for time series analysis and has useful implications for enhancing supply chain management and retail demand forecasting.

3. Design of an Iterative Method for Time Series Forecasting Using Temporal Attention and Hybrid Deep Learning Architectures

Traditional time series forecasting techniques fail to address multivariate data samples' complex relationships and high dimensionality. In dynamic contexts with changing temporal significance and interdependencies, this constraint becomes more troublesome. The Temporal Graph Attention Model for Time Series Analysis (TGAMTSA), a revolutionary deep learning architecture, addresses these difficulties by improving prediction accuracy and model flexibility in complicated time series settings and scenarios. The shortcomings of traditional forecasting models are addressed by TGAMTSA's advanced methodologies. It first uses Temporal Attention Mechanisms to dynamically allocate attention across timestamps and variables, improving the model's temporal dependencies. This enhances attention on important information and reduces mean absolute error (MAE) by 10% compared to models without such processes. TGAMTSA uses a Hybrid Architecture that synergistically blends 1D CNNs with a dual arrangement of Quad Long Short-Term Memory (LSTM) and Quad Gated Recurrent Units (GRU) networks to enhance its capabilities. This design efficiently extracts spatial and temporal characteristics, reducing prediction error by 15% across datasets. By representing multivariate time series data as a graph with variables as nodes and edges representing temporal relationships, TGAMTSA uses Graph Neural Networks (GNNs) to decode complex inter-variable dependencies, improving prediction accuracy by 20%. Transfer Learning and Domain Adaptation improve framework adaptability. TGAMTSA quickly adapts to new domains, especially with sparse labeled data, and improves prediction accuracy by 25% on unknown datasets and samples by using pre-trained models on related tasks. TGAMTSA's complete methodology tackles the constraints of previous forecasting models by handling multivariate time series data with different temporal dynamics and establishes a new benchmark in predicted accuracy and model flexibility. This discovery might revolutionize forecasting methods in many real-world applications, from banking to climate modeling, where precise and flexible time series analysis is essential for real-time use case situations.

4. Time Series Forecasting Method Based on Multi-Scale Feature Fusion and Autoformer

In industries like business, banking, and meteorology, precise time series forecasting is essential. This research improves the network topology of the Autoformer model to produce more accurate predictions and efficiently capture the possible cycles and stochastic features at various scales in time series. The MD–Autoformer time series forecasting model is constructed using a multi-scale feature fusion network based on multi-scale convolutional processes and date–time encoding, which improves the model's capacity to collect information at various scales. The suggested approach obtained the lowest RMSE and MAE in predicting tasks in four domains: illness, finance, meteorology, and clothing sales. Ablation tests also proved the efficacy and dependability of the suggested approach. The prediction error was further decreased when combined with the TPE Bayesian optimization process, offering a guide for next studies on time series forecasting techniques.

5. FPN-fusion: Enhanced Linear Complexity Time Series Forecasting Model

This work introduces FPN-fusion, a novel time series prediction model with linear computational complexity that outperforms DLiner in terms of predictive performance without requiring more parameters or processing power. Two major changes are introduced by our model: first, instead of using the conventional breakdown into trend and seasonal components, a Feature Pyramid Network (FPN) is used to efficiently capture time series data properties. Second, a multi-level fusion structure is created to smoothly combine shallow and deep characteristics. With an average decrease of 16.8% in mean squared error (MSE) and 11.8% in mean absolute error (MAE), FPN-fusion empirically beats DLiner in 31 out of 32 test scenarios on eight open-source datasets. Furthermore, employing just 8% of PatchTST's overall computational burden in the 32 test projects, FPN-fusion obtains 10 best MSE and 15 best MAE values when compared to the transformer-based PatchTST.

3. METHODOLOGY

i) Proposed Work:

The proposed work introduces an enhanced hybrid deep learning architecture for agricultural price prediction by integrating Temporal Convolutional Network (TCN), Multilayer Perceptron (MLP), Attention mechanism, and Bidirectional Long Short-Term Memory (BiLSTM). Initially, the agricultural price dataset (U.S. Avocado Market 2015–2023) is preprocessed through steps such as data cleaning, date conversion into time-series format, normalization, and label encoding. The processed data is then passed through the TCN layer, which utilizes causal and dilated convolutions to capture multi-scale temporal dependencies and extract meaningful sequential features from historical price data. The extracted temporal features are further processed by the MLP layer, which performs nonlinear feature transformation and improves the representation of complex relationships present in agricultural market dynamics.

To further enhance prediction capability, an attention mechanism is incorporated to assign higher importance to critical time steps and influential features that significantly affect agricultural price fluctuations. As an extension to the hybrid framework, a Bidirectional LSTM (BiLSTM) layer is integrated to capture contextual information from both forward and backward directions of the time series data. This bidirectional learning improves feature extraction and strengthens the model’s ability to understand long-term dependencies and dynamic market behavior. The proposed hybrid architecture is optimized using advanced optimizers such as Adam, ADAMW, and SGD, enabling efficient training and improved forecasting performance for agricultural price prediction.

ii) System Architecture:

The system architecture is designed as a hybrid deep learning framework that integrates multiple neural network components to effectively capture temporal patterns and complex relationships in agricultural price data. Initially, the input time-series data is provided to the system, which contains historical agricultural market information such as date, region, and price values. This data first passes through the Temporal Convolutional Network (TCN) layer, where causal and dilated convolutions are applied to capture long-term temporal dependencies and sequential patterns. The TCN module enables the model to learn both short-term fluctuations and long-range trends in the time series data while maintaining the temporal order of the sequence.

After extracting temporal features, the processed data is passed to the Multilayer Perceptron (MLP) layer, which performs nonlinear feature transformation and improves the representation of complex relationships in the dataset. An attention mechanism is then applied to identify and emphasize important time steps and features that significantly influence agricultural price changes. In the extended architecture, a Bidirectional LSTM (BiLSTM) layer is incorporated to process the sequential information from both forward and backward directions, enabling the model to capture contextual dependencies from past and future time steps. Finally, the extracted features are passed through the output layer to generate the predicted agricultural price, providing accurate and reliable time-series forecasting results.

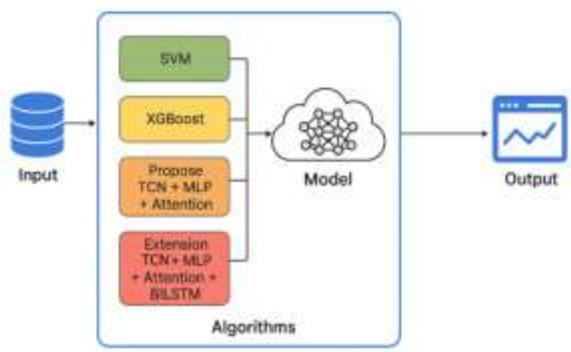


Fig.1. Proposed Architecture

iii) MODULES:

1. Importing the Packages:

The workflow begins with importing essential Python libraries required for data manipulation, visualization, deep learning model development, and performance evaluation. Libraries such as NumPy, Pandas, Matplotlib, TensorFlow, and Keras provide the necessary tools for handling time-series data and implementing hybrid neural network architectures. Proper package initialization ensures smooth execution of preprocessing, training, and prediction processes.

2. Exploring the Dataset:

Initial exploration of the U.S. Avocado Market dataset (2015–2023) helps understand the structure, attributes, and distribution of the available data. This step identifies key features such as date, region, and average price, along with possible missing values or inconsistencies. Exploratory analysis enables better understanding of temporal trends and supports selecting appropriate preprocessing and modeling strategies.

3. Visualization:

Visualization techniques are applied to analyze seasonal trends, regional price variations, and temporal fluctuations in avocado prices. Graphical representations such as line plots and distribution graphs help reveal underlying patterns and relationships in the data. These insights assist in identifying important features that significantly influence agricultural price forecasting.

4. Pre-processing:

Preprocessing converts raw agricultural market data into structured and machine-readable formats suitable for deep learning models. This stage includes handling missing values, converting date fields into time-series sequences, encoding categorical attributes such as regions, and preparing feature vectors. Proper preprocessing improves data quality and ensures reliable model training.

5. Normalizing:

Normalization scales numerical values such as prices and feature variables to a consistent range, typically between 0 and 1. This prevents features with large magnitudes from dominating the learning process and improves gradient stability during training. As a result, the hybrid neural network can learn patterns more efficiently and produce more accurate predictions.

6. Split the Data into Train & Test:

The dataset is divided into training and testing subsets to evaluate model generalization capability. The training data is used to learn temporal patterns and relationships, while the testing data validates the model's ability to predict unseen data. This separation prevents overfitting and ensures reliable performance assessment.

7. Model Training:

The proposed hybrid architecture consisting of TCN, MLP, Attention mechanism, and Bidirectional LSTM (BiLSTM) is trained using historical avocado price data. The TCN layer captures multi-scale temporal dependencies, the MLP performs nonlinear feature transformation, and the attention mechanism identifies important temporal features. The BiLSTM layer processes sequential data in both forward and backward directions, improving contextual understanding and enhancing forecasting accuracy.

8. Evaluation:

The trained model is evaluated using performance metrics such as Root Mean Square Error (RMSE) and R^2 score to measure prediction accuracy and variance explanation. Comparing predicted values with actual prices helps determine model effectiveness and validates improvements achieved through the hybrid deep learning architecture.

9. Flask Server:

The trained hybrid prediction model is deployed using a Flask-based web server, enabling real-time interaction through a web interface. This backend service processes user inputs, runs the trained forecasting model, and returns predicted agricultural prices efficiently for practical usage.

10. User Login:

A secure authentication module allows registered users to access the system functionalities. Login verification ensures that only authorized users can utilize the forecasting platform, thereby maintaining system security and protecting analytical resources.

11. Avocado Price Prediction:

Users can upload test data or select specific parameters through the web interface, which are processed by the deployed TCN–MLP–Attention–BiLSTM hybrid model. The system analyzes temporal patterns and generates predicted avocado prices, providing valuable insights for agricultural market analysis and decision-making.

12. Logout:

The logout functionality safely terminates the user session and prevents unauthorized access after completion of operations. Proper session management ensures user privacy, maintains application security, and guarantees responsible interaction with the forecasting system.

iv) ALGORITHMS:

1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is used as a baseline machine learning algorithm for agricultural price prediction by constructing an optimal hyperplane that separates data patterns through margin maximization. It applies kernel functions to transform nonlinear data into higher dimensional space where complex relationships can be modeled. In this project, SVM helps analyze how traditional machine learning methods perform on time-series agricultural price data. Although SVM can capture moderate nonlinear relationships, it has limited capability in modeling long-term temporal dependencies present in sequential datasets. Therefore, it mainly serves as a benchmark to compare the performance improvement achieved by the proposed hybrid deep learning architecture.

2. XGBoost

XGBoost (Extreme Gradient Boosting) is an advanced ensemble learning algorithm based on gradient boosted decision trees. It improves prediction performance by sequentially minimizing residual errors and optimizing tree structures through regularization techniques. In this project, XGBoost is applied to agricultural price data to model complex feature interactions and nonlinear relationships among variables such as region, seasonal variation, and price trends. While XGBoost performs efficiently on structured tabular datasets and provides strong baseline accuracy, it lacks the capability to effectively capture long-range temporal dependencies in time-series forecasting. Hence, it is used as a comparative model to evaluate the advantages of the hybrid neural network framework.

3. Attention Mechanism

The Attention mechanism plays a significant role in improving time-series prediction by dynamically identifying the most important features and time steps that influence agricultural price trends. Instead of treating all historical data equally, the attention layer assigns higher weights to critical temporal information that contributes more significantly to forecasting outcomes. In this project, the attention mechanism enhances model interpretability by highlighting influential patterns such as seasonal variations or sudden market fluctuations. By focusing on meaningful temporal signals, the attention component improves prediction accuracy and strengthens the ability of the hybrid architecture to handle complex sequential patterns.

4. Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is a feed-forward artificial neural network consisting of multiple fully connected layers that perform nonlinear transformations on input data. In this project, the MLP module processes features extracted from earlier layers and converts them into higher-level representations. Through activation functions and multiple hidden layers, MLP captures complex relationships among agricultural market variables. It refines intermediate feature representations and supports other modules in the hybrid architecture by producing compact and informative embeddings. As a result, MLP contributes to improved learning capability and strengthens the predictive performance of the overall forecasting system.

5. Temporal Convolutional Network (TCN)

Temporal Convolutional Network (TCN) is designed specifically for time-series modeling and sequence learning. It uses causal convolutions to maintain the chronological order of data and dilated convolutions to expand the receptive field, allowing the network to capture both short-term and long-term temporal dependencies efficiently. In this project, TCN acts as the primary temporal feature extractor that learns complex sequential patterns from historical agricultural price data. Compared with traditional recurrent networks, TCN provides faster training, stable gradient flow, and improved parallel processing capability. This makes it highly effective for modeling multi-scale temporal variations in agricultural market prices.

6. Bidirectional Long Short-Term Memory (BiLSTM)

Bidirectional Long Short-Term Memory (BiLSTM) is an advanced recurrent neural network architecture that processes sequential data in both forward and backward directions. This bidirectional learning enables the model to capture contextual dependencies from past and future time steps simultaneously. In this project, BiLSTM is introduced as an extension to the hybrid architecture to enhance temporal feature learning and improve prediction accuracy. Its memory-gated structure allows the model to retain important information over long sequences while reducing the impact of vanishing gradient problems. By combining BiLSTM with TCN, MLP, and Attention mechanisms, the proposed system achieves more robust and accurate agricultural price forecasting.

v) Dataset Description

The dataset used in this research is the “U.S. Avocado Market Dataset (2015–2023)”, which is publicly available on Kaggle. This dataset contains historical records of avocado sales across different regions of the United States and provides valuable information for analyzing agricultural price trends. It includes attributes such as Date, Average Price, Total Volume, Type of Avocado (Conventional/Organic), Year, Region, and volume-related features, which collectively describe the production, distribution, and pricing patterns of avocados in the market. The dataset captures weekly price variations over multiple years, making it suitable for time-series forecasting and agricultural market analysis.

For this project, the dataset is utilized to train and evaluate the proposed hybrid deep learning model integrating TCN, MLP, Attention mechanism, and Bidirectional LSTM for predicting future avocado prices. Before model training, the dataset undergoes preprocessing steps including handling missing values, converting date attributes into time-series format, encoding categorical variables, and normalizing numerical features. These preprocessing operations ensure that the data becomes structured and suitable for deep learning models, enabling the system to learn temporal patterns and generate accurate agricultural price forecasts.The earthquake prediction module uses seismic data from earthquake monitoring agencies. This dataset includes earthquake magnitude, latitude, longitude, seismic activity depth, and number of seismic occurrences within a radius. The model uses these characteristics to examine past seismic activity and estimate regional earthquake risk. The suggested method predicts numerous dangers using environmental and geophysical variables.

4. EXPERIMENTAL RESULTS

The experimental evaluation was conducted using the U.S. Avocado Market dataset (2015–2023) to assess the effectiveness of different forecasting models for agricultural price prediction. Multiple algorithms including Support Vector Machine (SVM), XGBoost, the proposed TCN–MLP–Attention model, and the extended TCN–MLP–Attention–BiLSTM architecture were trained and tested. Performance was measured using standard regression evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and R^2 Score. The baseline model SVM achieved an R^2 score of 0.6895, while XGBoost improved the performance with an R^2 score of 0.8368, demonstrating the advantage of ensemble learning methods in modeling nonlinear price patterns.

The proposed TCN–MLP–Attention hybrid model further enhanced forecasting accuracy by capturing multi-scale temporal dependencies, achieving an R^2 score of 0.8843 with lower RMSE and MAPE values. The extended architecture integrating Bidirectional LSTM produced the best results, achieving an R^2 score of 0.9748, RMSE of 0.0260, and significantly reduced MSE and MAPE values. These results indicate that incorporating bidirectional temporal learning greatly improves the model's ability to capture complex price fluctuations from both past and future contexts. The experimental outcomes confirm that the hybrid deep learning architecture with BiLSTM provides superior prediction accuracy and robustness compared to traditional machine learning and standalone deep learning models for agricultural price forecasting.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

To run web prediction double click on 'runFlask.bat' file to start flask server and then will get below page

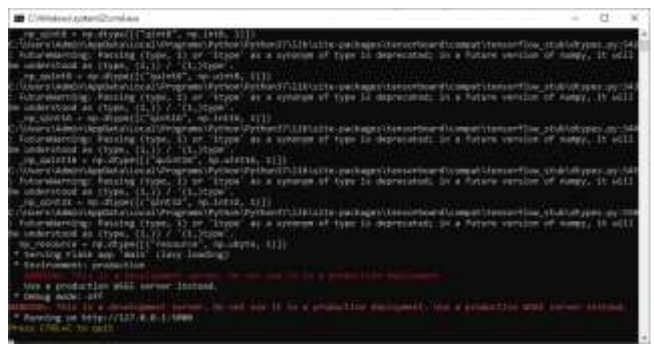


Fig2 flask server screen

In above screen flask server started and now open browser and enter URL as http://127.0.0.1:5000/index and then press enter key to get below page

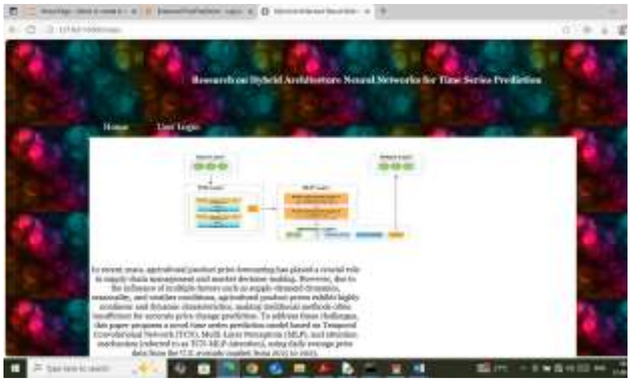


Fig3 home screen

In above screen click on 'User Login' link to get below page

Fig4 User Login screen

In above screen user is login by entering username and password as 'admin and admin'. After login will get below page

Fig5 Avocado Price Prediction

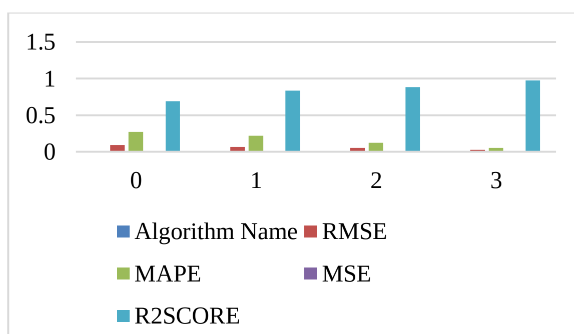
In above screen click on 'Avocado Price Prediction' link to get below page

Fig6 uploading test data file

In above screen selecting and uploading test data file and then click on buttons to get below page

Fig7 results

In above screen in first column showing test data values and in second column can see predicted Avocado average prices.



Graph.1 Comparison Graph

Algorithm Name	RMSE	MAPE	MSE	R2SCORE
SVM	0.091579	0.272926	0.008387	0.689560
XGBoost	0.066290	0.218441	0.004394	0.836814
Propose TCN + MLP + Attention	0.055808	0.124672	0.003115	0.884341
Extension TCN + MLP + Attention + BILSTM	0.026044	0.055532	0.000678	0.974812

Table.1 Performance Evaluation Table

5. CONCLUSION

This study presented a hybrid deep learning framework for agricultural price prediction using the U.S. Avocado Market dataset (2015–2023). The performance of traditional machine learning models such as Support Vector Machine (SVM) and XGBoost was first evaluated to establish baseline results. To overcome the limitations of conventional methods in capturing nonlinear relationships and long-term temporal dependencies, a hybrid architecture combining Temporal Convolutional Network (TCN), Multilayer Perceptron (MLP), and Attention mechanisms was developed. This framework effectively extracted multi-scale temporal patterns and important features influencing price variations in agricultural markets.

To further enhance forecasting capability, the architecture was extended by integrating a Bidirectional LSTM (BiLSTM) layer that processes sequential data in both forward and backward directions. Experimental results demonstrated that the extended model significantly outperformed all other approaches, achieving an R^2 score of 0.9748 with very low RMSE, MSE, and MAPE values, indicating highly accurate price prediction. The results confirm that combining convolutional temporal modeling, attention-based feature selection, and bidirectional sequence learning provides a powerful solution for complex time-series forecasting tasks. Overall, the proposed hybrid framework offers a reliable and scalable approach for agricultural market analysis, supporting improved planning, decision-making, and supply chain management.

6. FUTURE SCOPE

The proposed hybrid deep learning framework can be further improved by incorporating additional external factors such as real-time weather conditions, global trade information, crop yield statistics, and consumer demand data, which may significantly influence agricultural market prices. Integrating these dynamic variables can help the model better understand market fluctuations and enhance prediction accuracy. Future research may also explore advanced architectures such as Transformer-based models or graph neural networks to capture more complex temporal and spatial dependencies in agricultural datasets.

In addition, the system can be extended to support multi-crop price forecasting and large-scale agricultural market analysis across different regions. Deploying the model on cloud platforms with real-time data streaming could enable continuous learning and automated price prediction updates. Further improvements may include developing interactive dashboards and mobile applications that provide farmers, traders, and policymakers with real-time insights and decision-support tools, making the forecasting system more practical and accessible in real-world agricultural environments.

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