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Sales Volume and Price Prediction Using Attention-Based RW-FN-BiLSTM Framework

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Abstract: In the era of big data, accurate sales volume and price prediction is crucial for enterprises' market decision-making, inventory management, and pricing strategies. Traditional methods often fail to capture complex temporal patterns and nonlinear relationships in sales data, whereas deep learning offers promising solutions. This study proposes an Attention-based RW-FN-BiLSTM hybrid neural network to improve prediction accuracy. Using a 2015–2023 Hass Avocado Board dataset, covering multiple regions and key variables like the price and sales volume of conventional and organic avocados, the model integrates BiLSTM for long-term dependencies, RW-FN for feature extraction, and an Attention mechanism for adaptive weight allocation to key features. Experimental results show stable convergence, with predicted values closely following actual trends and an error distribution indicating strong generalization. While some deviations exist, further optimization in network structure and feature selection can enhance performance. This study validates the Attention-based RW-FN-BiLSTM model, providing enterprises with a data-driven approach to market trend analysis, inventory optimization, and pricing decisions, helping them make precise strategic choices in a competitive market environment.

Keywords: Sales Prediction, Attention-based RW-FN BiLSTM, Time Series Data, Deep Learning, Data Characteristics, RW-FN

1. Introduction

In the AI+ market sales era, accurate sales volume and price prediction are essential for businesses to optimize inventory, production, and resource allocation while enhancing strategic decision-making and market competitiveness. The avocado market, a growing segment of the global food industry, has seen rising demand due to increasing consumer awareness of its nutritional benefits. However, market dynamics are becoming increasingly complex due to factors such as seasonality, regional preferences, and the expanding organic avocado sector, making precise forecasting a critical challenge.

Sales forecasting is inherently complex, influenced by dynamic factors like consumer behavior, market trends, seasonality, and economic conditions. Traditional statistical and machine learning methods often fail to capture the long-term dependencies and nonlinear relationships in time-series data. BiLSTM (Bidirectional Long Short-Term Memory) networks effectively model long-term dependencies while addressing RNNs' vanishing gradient problem. However, BiLSTM alone may

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not fully capture intricate sales patterns. RW-FN (Random Weight Functional Link Network) enhances feature extraction by establishing direct input-output connections, improving the model's ability to capture nonlinear relationships. Additionally, the Attention Mechanism (AM) allows the model to focus on critical features, improving prediction accuracy and interpretability.

This study proposes an Attention-based RW-FN-BiLSTM hybrid framework for sales volume and price prediction, leveraging a 2015–2023 dataset from the Hass Avocado Board. The dataset spans multiple regions and key variables, including sales volume, price, cost, and revenue of conventional and organic avocados. This paper details the dataset's characteristics, the model architecture, and the roles of BiLSTM, RW-FN, and Attention Mechanism in enhancing predictive performance, followed by an evaluation of the model's forecasting accuracy and effectiveness.

2. Literature Review

In the AI+market sales context, accurate forecasting of agricultural product sales volume and price is crucial for optimizing inventory, supply chain scheduling, and pricing strategies. Deep learning-based time series forecasting methods have significantly advanced in this field, offering valuable insights. This study leverages these advancements to develop an Attention-based RW-FN-BiLSTM model for avocado sales volume and price prediction.

Sun F et al. systematically reviewed agricultural price forecasting methods, classifying traditional and deep learning techniques, providing a foundational research framework for this study [1]. Kurumatani K applied Recurrent Neural Networks (RNNs) for time series forecasting, demonstrating their ability to capture sequential dependencies, which informs the model evaluation and optimization in this study [2].

Kamilaris A and Prenafeta-Boldú F X explored Convolutional Neural Networks (CNNs) in agriculture, emphasizing their feature extraction capabilities, which inspire the integration of CNN-like approaches for avocado market data analysis [3]. Wan R et al. introduced a Multivariate Temporal Convolutional Network (MTCN), guiding this research in handling multiple factors like avocado size and classification for improved forecasting accuracy [4].

Dudukcu H V et al. combined Temporal Convolutional Networks (TCNs) with RNNs for chaotic time series prediction, offering insights into addressing nonlinearity and uncertainty in avocado prices [5]. Hewage P et al. used TCNs for weather forecasting, providing transferable techniques in time series preprocessing and model optimization, particularly for handling external influences on sales [6].

He Y and Zhao J applied TCNs for anomaly detection, which aids in identifying abnormal price fluctuations and improving model robustness [7]. Lim B and Zohren S reviewed deep learning for time series forecasting, summarizing emerging trends and ensuring the methodological advancement of this study [8]. Attention mechanisms play a critical role in enhancing deep learning models for price forecasting. Gu Y H et al. applied a Dual-Input Attention LSTM to agricultural prices, highlighting the attention mechanism's ability to focus on key influencing factors, which directly informs this study's model design [9].

This research utilizes the 2015-2023 dataset from the Hass Avocado Board, covering price, sales volume, and other variables across multiple regions. By integrating the sequential modeling capabilities of BiLSTM, RW-FN's feature extraction strengths, and attention mechanisms for critical factor identification, this study develops an advanced forecasting model, aiming to improve accuracy and reliability in avocado market prediction, ultimately benefiting market analysis, inventory management, and pricing strategies.

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3. Data Introduction

The study leverages a 2015–2023 Hass Avocado Board dataset, covering weekly price and sales volume across 54 U.S. regions, including major metro areas. It enables both micro- and macro-level market analysis. Key variables include average unit price, total sales volume, and size-specific volumes (PLU codes: 4046, 4225, 4770). The dataset also distinguishes conventional vs. organic avocados, facilitating comparative analysis. While some packaging format data contain missing values, core price and volume metrics remain highly reliable. Its nine-year temporal span and geographic breadth provide insights into price fluctuations, consumption trends, and regional variations, supporting time-series forecasting and market trend analysis. This dataset serves as a robust foundation for predictive modeling, pricing strategies, and inventory optimization.

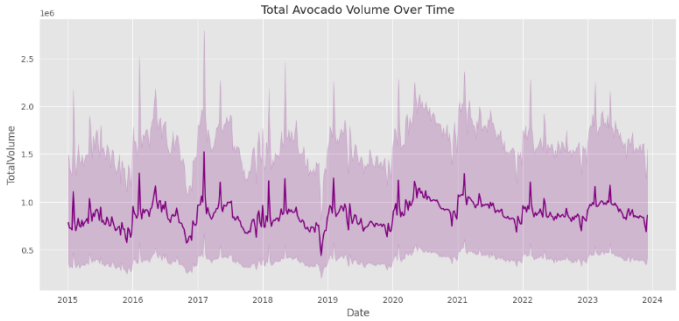

Figure 1: Total Avocado Volume Over Time

Figure 1 presents the total volume of avocados over the period from 2015 to 2024. It shows the variation in the quantity of avocados available in the market over time. We can observe the fluctuations in the volume, which might be affected by factors such as seasonality, production levels, and consumer demand. By analyzing this graph, we can gain insights into the general trends of avocado supply in the market during this time frame.

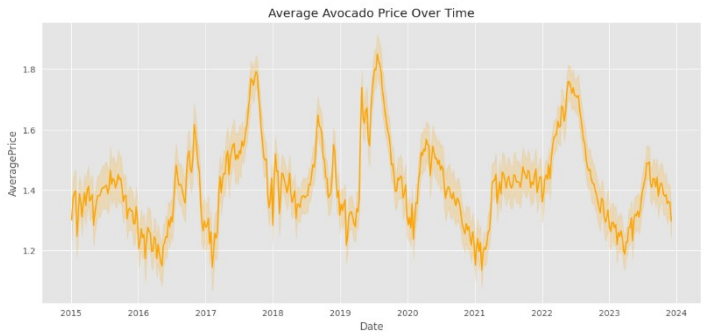

Figure 2: Average Avocado Price Over Time

Figure 2 presents the average price of avocados is depicted over the years from 2015 to 2024. It allows us to see how the price of avocados has changed over time. The graph might reveal trends related to market dynamics, such as the influence of supply and demand imbalances, production costs, and external factors like economic conditions. We can study the upward or downward movements of the price curve to understand the price behavior of avocados in the market.

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4. LSTM-RVFL-Attention Model

4.1. LSTM Layer

The Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) specifically designed to address the challenges of capturing long-term dependencies in sequential data. Unlike traditional RNNs, which often suffer from vanishing or exploding gradient problems, LSTMs introduce a memory cell and three gating mechanisms (input gate, forget gate, and output gate) to regulate the flow of information. This architecture allows LSTMs to selectively retain or discard information over time, making them particularly effective for modeling time series data with complex temporal patterns and nonlinear relationships. Figure 3 shows the structure of LSTM.

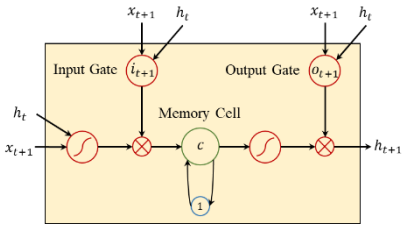

Figure 3: The structure of LSTM

4.2. RW-FN Layer

The Random Weight Functional Link Network (RW-FN) is a feedforward neural network that enhances feature extraction by assigning random weights to input-hidden layer connections, reducing computational complexity while capturing nonlinear patterns. Unlike traditional networks requiring extensive training, RW-FN transforms input features into higher-dimensional spaces using nonlinear activation functions and trains the output layer via linear regression. Figure 4 presents the structure of RW-FN.

In sales volume and price prediction, RW-FN addresses limitations of traditional methods by enriching feature representation without extensive training. When integrated with BiLSTM and Attention mechanisms, RW-FN introduces nonlinearity and diversity, capturing complex temporal patterns and focusing on critical features. This synergy improves prediction accuracy and generalization, as shown by symmetrical error distribution in experiments. The model's efficiency and adaptability make it ideal for large-scale datasets like avocado market data, offering enterprises a robust tool for market analysis and decision-making.

RW-FN Layer:

$$\text{Output} = \text{ReLU}(W_{\text{rvfl}} \cdot h_t + b_{\text{rvfl}}) \tag{1}$$

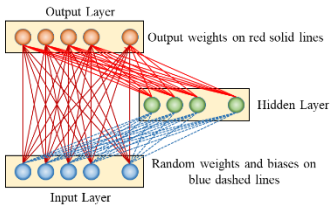

Figure 4: The structure of RW-FN

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4.3. Attention Mechanism

The Attention mechanism is a computational model that dynamically assigns adaptive weights to input features or time steps, allowing the model to focus on the most relevant information. Unlike traditional methods that treat all data equally, Attention calculates importance scores using a learnable function and normalizes them via softmax to prioritize critical features. Figure 5 illustrates the structure of Attention Mechanism.

In sales volume and price prediction, Attention enhances performance by focusing on key drivers such as seasonal trends, price changes, or regional variations, while reducing noise. When integrated with BiLSTM and RW-FN, Attention selectively emphasizes impactful features extracted by these components, improving the model's ability to capture complex patterns. This synergy results in stable convergence and symmetrical error distribution, as shown in experiments. However, further optimization in feature selection could enhance accuracy. Overall, Attention provides a powerful tool for enterprises to analyze market trends and make data-driven decisions.

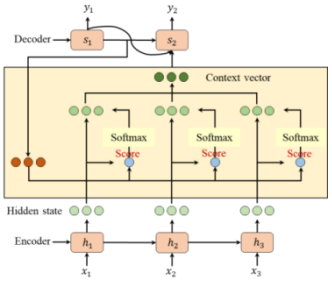

Figure 5: The structure of AM

4.4. Overall framework

The Attention-based RW-FN-BiLSTM hybrid model integrates three key technologies for sales volume and price prediction in complex time-series data. BiLSTM captures bidirectional dependencies, analyzing both past price trends and future influences (e.g., holiday promotions). A key innovation is the attention mechanism, which dynamically assigns importance weights to critical time steps or features. For instance, it amplifies the impact of sales peaks or extreme weather events, improving focus on key data and enhancing prediction accuracy. Figure 6 illustrates the model's structural framework. This hybrid approach ensures efficient, accurate, and interpretable forecasting, making it highly effective for market trend analysis and pricing strategies.

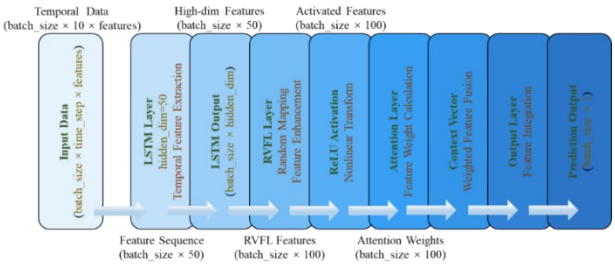

Figure 6: Model Structure

5. Model result analysis

The analysis of our Attention-based RW-FN-BiLSTM hybrid model's performance in predicting avocado prices reveals compelling results across multiple dimensions of evaluation. Through comprehensive examination of both visual representations and quantitative metrics, we observe that

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the model demonstrates strong predictive capabilities while maintaining robust performance across different market conditions.

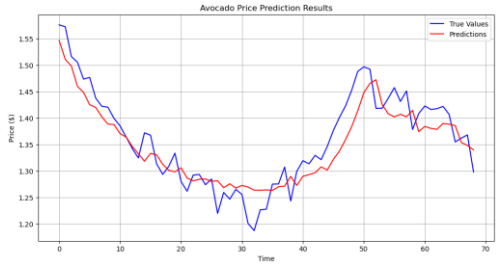

Figure 7: Avocado Price Prediction Results

Figure 7 presents the avocado price prediction results, demonstrating the model's strong generalization ability across market conditions. Low MSE, RMSE, and MAE values indicate high predictive accuracy, while the R^2 score confirms the model effectively explains price variance.However, the model shows minor limitations, including a slight lag in responding to sudden price shifts and a tendency to underestimate peaks and overestimate troughs. These suggest room for improvement in capturing extreme price fluctuations.

The Attention-based RW-FN-BiLSTM model effectively balances long-term trend detection with short-term price sensitivity. The attention mechanism enhances focus on key historical patterns, while BiLSTM efficiently processes sequential price data. This synergy results in a robust, reliable forecasting framework, making it highly valuable for market analysis and pricing strategy development.

Table 1: Comparison of ablation experimental results

Model	MSE	MAE	RMSE
Attention-based LSTM-RW-FN	**0.0175**	**0.1016**	**0.1356**
LSTM	0.0256	0.1346	0.1564
Attention-based-LSTM	0.0578	0.1900	0.2304
LSTM-RW-FN	0.1865	0.3987	0.4239
RNN	0.0289	0.1479	0.1618

Table 1 compares the performance of different models using metrics such as MSE, MAE, and RMSE. The Attention-based RW-FN-BiLSTM hybrid model outperforms the LSTM, RNN, LSTM-RW-FN, and Attention-based LSTM models, achieving lower error values across all metrics.

6. Conclusions

This study presents a sales volume and price prediction model based on the Attention-based RW-FN-BiLSTM framework, integrating BiLSTM for time series modeling, RW-FN for nonlinear feature extraction, and the Attention mechanism for focusing on key patterns. Using a 2015–2023 dataset from the Hass Avocado Board, covering multiple regions and variables such as price and volume of conventional and organic avocados, the model is validated through extensive experiments.Results show that the model effectively captures market trends and fluctuations, outperforming traditional methods in accuracy and generalization. However, it exhibits a slight lag in responding to sudden

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price shifts and has biases in extreme values, occasionally underestimating peaks and overestimating troughs.

Future research can focus on enhancing responsiveness to sharp price changes by incorporating external factors (e.g., weather, economic indicators) and refining the model's architecture. Exploring Graph Neural Networks (GNNs) or Variational Autoencoders (VAEs) may further improve adaptability.Overall, this study introduces an advanced deep learning approach for avocado sales volume and price forecasting, providing valuable insights for agricultural market analysis, inventory management, and pricing strategies.

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